A Proposed Framework for Supply Chain Analytics using Customer Data

Nteboheng Pamella Phadi

29023051

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Table of Abbreviations

Abbreviation	Description
APICS	American Production and Inventory Control Society
B2B	Business-to-Business
B2C	Business-to-Customer
BCI	Business Confidence Index
BDA	Big Data Analytics
BER	Bureau of Economic Research
CCI	Consumer Confidence Index
CPS	Cyber-Physical Systems
CRM	Customer Relationship Management
DSC	Digital Supply Chain
EDI	Electronic Data Interchange
EIA	Energy Information Administration
ERP	Enterprise Resource Planning
ETL	Extraction, Transformation and Loading
GPS	Global Positioning systems
GSCPI	Global Supply Chain Pressure Index
IoT	Internet of Things
ISN	Intertwined Supply Network
PC	Petrochemicals Company
POS	Point of Sales
RFID	Radio Frequency Identification
SCA	Supply Chain Analytics

SCC	Supply Chain Council
SCM	Supply Chain Management
SCOR	Supply Chain Operations Reference
SCR	Supply Chain Resilience
SCRM	Supply Chain Risk Management
SEM	Structural Equation Model
TMS	Transport Management System
WTI	West Texas Intermediate

Dedication

I would like to dedicate this thesis to my son, Leruo. Thank you for being my inspiration.

Acknowledgements

First and foremost, I would like to thank God for giving me the strength, diligence and perseverance.

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Abstract

The COVID-19 pandemic and recent geopolitical events have called for a need to re-evaluate methodologies for Supply Chain Risk management. Significant investment in supply chain technology has resulted in data being generated throughout the value chain. Customer data, specifically, is of interest in order to establish customer-centricity and an enhanced customer journey. However, the transformation of this data to insight is not obvious for some organisations. Forecasting models are typically used to inform decision-making, mitigate risks and enlighten policymakers. This thesis aims to address this challenge by proposing a set of capabilities that will enhance the integration of the supply chain network to its customer data. Given this context, two methodologies were used to address the research problem; (i) multinational petrochemicals company was considered for our case study and a web-based survey was distributed among key stakeholders at their head offices in South Africa. A structured equation model (SEM) was constructed to empirically test the proposed relationships among the constructs, specifically: People, Process and Technology capabilities; (ii) The macro-economic factors that drive customer demand also considered. Increasing crude oil prices have increased logistics costs and have incited the deglobalization of supply chain operations. A novel petroleum forecasting model is also proposed, particularly focusing on the forecasting on South Africa's petrol and diesel consumptions. The model uses indices for Brent crude oil price (ZAR), Gross Domestic Product (GDP), Rand to Dollar exchange rate, Consumer Confidence Index (CCI) and Business Confidence Index (BCI) data as input data. Overall, this study suggests that in order to effectively serve their customers, organisations need to establish a culture of customer centricity that is underpinned by appropriate supply chain analytics techniques. The predictive model further highlights the need to establish the relationship between the organisation's supply chain and micro and macro-economic drivers.

1 INTRODUCTION

1.1 Background Information

Supply Chain Management (SCM) and its definition has evolved over the years. Early literature includes definitions by Cooper, Lambert, and Pagh, (1997(8):2), where SCM is defined as, *the end-to-end business process integration that occurs between end user and suppliers of products, services and information that add value to customers*. More recent definitions of SCM view it as: *the synchronization of production, inventory, location and transportation functions between the key stakeholders that exist in a supply chain in an effort to achieve the optimal receptiveness and productivity for the market being observed* (Hugos, 2018:29). In addition, a supply chain is concerned with the integration of interrelated business processes which comprise of the following operations: (1) acquisition of raw materials and parts, (2) the transformation of the raw materials and parts, and (3) the distribution of the finished products (Fahimnia, Farahani, Marian and Luong; 2013:1).

Overtime, the end-to-end business process integration has become increasingly digitalised and has deviated from the traditional supply chain view. Contemporary supply-chain networks are not only characterised by the integration of data sources but have also resulted in increased consumer-power. These supply chain networks consist of nodes and links, where the nodes are representative of a single organisation, and the links are characterised by the flow of information, material, and/or finance between organisations (Carter, Rogers and Choi, 2015). The supply chain network has metamorphosised into the digital supply network (DSN), comprising of technology driven, and interconnected open system supply operations, whose aim is to drive the physical act of production and distribution, see Figure 1 (Deloitte, 2016).

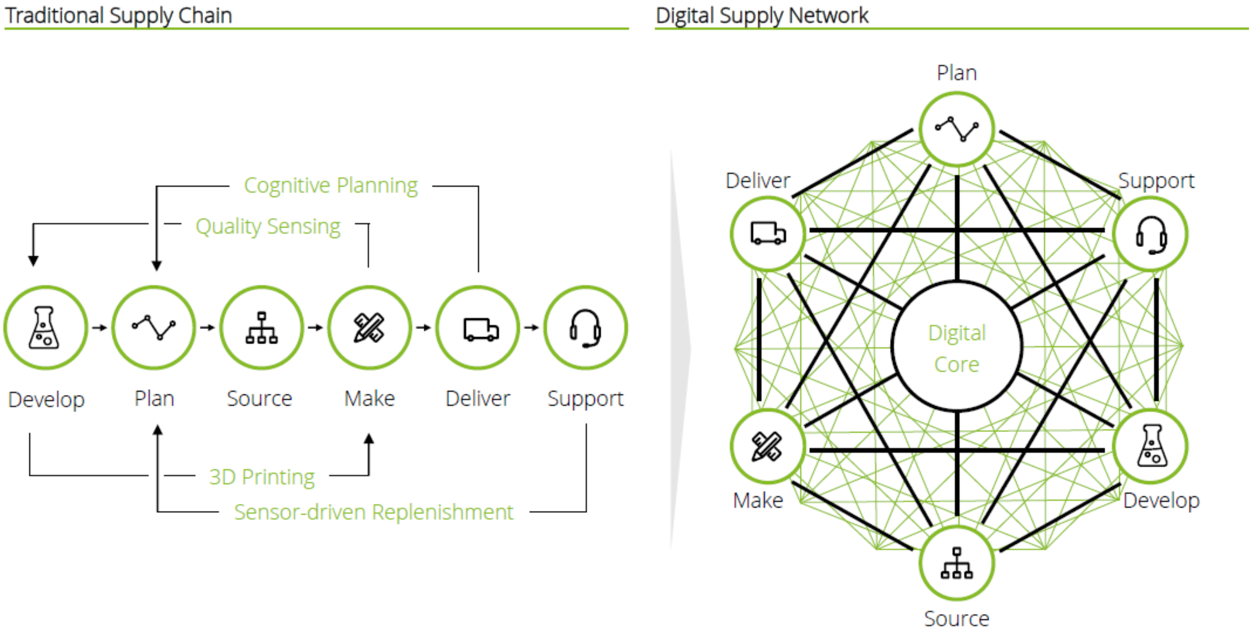

Figure 1: Traditional Supply Chain versus Digital Supply Chain Network (Deloitte, 2016).

The integration of the physical and technological systems across supply chain networks is also termed 'Supply Chain 4.0'. This concept is underpinned by technologies such as Internet of Things (IoT) and Cyber-Physical Systems (CPS) (Sobb, Turnbull, and Moustafa, 2020:2-4).

IoT comprises of intelligent and connected products which are connected through the internet environment and are self-configuring, and self-managing. The digital connection facilitates the automations and self-optimisation of goods and services, including the delivery of goods without human intervention. IoT comprises of system elements that make autonomous decisions and value networks decentralised.

The CPS environment comprises of interconnected ecosystems and collaborating entities of various forms which include both physical devices and humans, whose objective is to improve user experience (Nazarenko and Camarinha-Matos, 2017). The environment can be viewed in three layers: firstly, the automatic sensing and collecting of data in the physical space; secondly, the space where human behaviour is captured through cyber-space and examined for demand-changing patterns; and thirdly, the physical supply chain, whereby as the social status, and knowledge of humans evolve, so do the nature of their interactions and operations in this space (Ivanov *et al*., 2019:356).

Figure 2 is a graphical representation of Supply Chain 4.0 which comprises of two dimensions, namely: the physical supply chain dimension and the digital data value chain dimension (Hofmann and Rüsch., 2018).

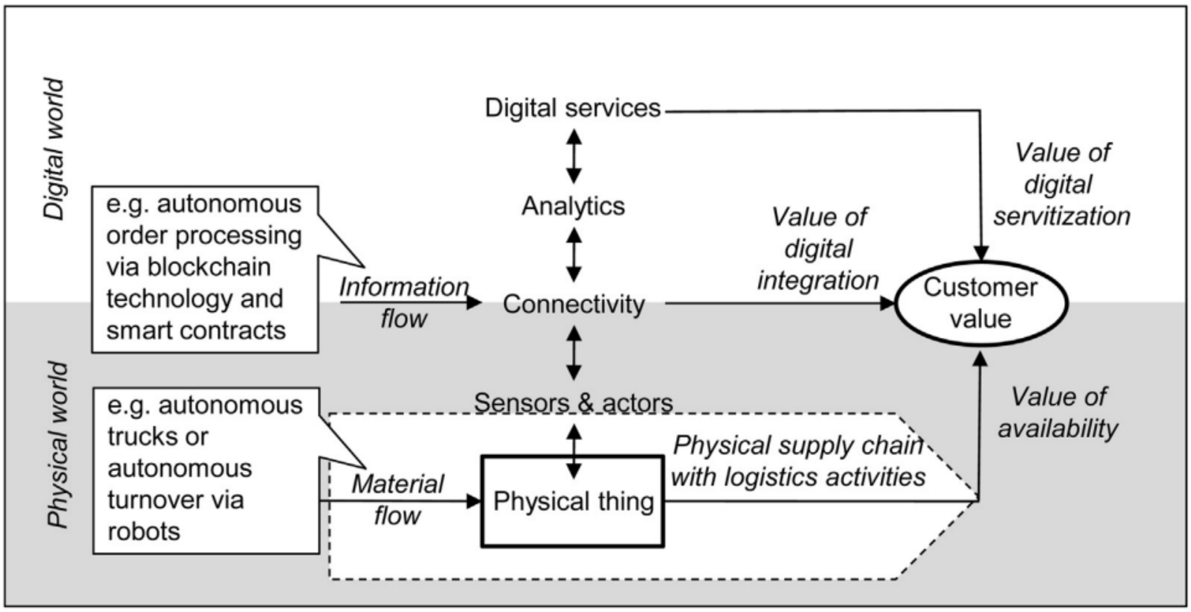

Figure 2: Supply Chain 4.0 dimensions (Hofmann and Rüsch, 2018).

1.2 Supply Chain Demand Planning and Forecasting

A paramount task in the digital supply chain (DSC) and technology driven ecosystem is the ability to assess and predict the state of production and resources. Supply chain activities are set into motion by customer demand and information is passed between supply chain actors upstream and is complemented by the flow of products downstream to ultimately fulfil customer demands. This demand is however not constant and therefore introduces supply chain uncertainty (Syntetos *et al*., 2016:2). To address the challenge of supply chain demand uncertainty, the Supply Chain

Operations Reference (SCOR®[1]) model directs to the use of Demand Planning and Forecasting, which involves the use of forecasting algorithms that enable the understanding and anticipation of customer demand (SCC, 2012). Demand Planning and Forecasting employs predictive analytics to understand consumer demand (Bon and Ng, 2017:2).

Demand planning and forecasting methods can either be quantitative or qualitative in nature. Forecasting methods can be classified into three categories, namely: judgemental, univariate and multivariate, which can either be qualitative or quantitative. Qualitative methods facilitate judgemental forecasting (Chatfield, 2000), and are dependent on the subjective inputs of subject-matter-experts and include, among others, panel consensus, Delphi studies and market research (Wang and Chen, 2019:3). Quantitative demand forecasting methods are data-driven and include methodology such as regression analysis and time series analysis, to name a few (Wang and Chen, 2019:3). In quantitative methodology, quantifiable measures of variables are collected using structured procedures and formal instruments, to make inferences about the population sample (Queirós *et al*., 2017:370).

In the case of quantitative demand forecasting methods, data that is available for analysis in supply chains can be categorised as either being small data or big data. Data that is definite, comprises of predefined dataset attributes, and that can typically be accumulated to a spreadsheet for analysis is referred to as small data; while big data refers to high data volume that can be both structured and unstructured which requires advanced analytical systems to access, organise, analyse and interpret (Miglani, 2016). The primary sources of supply chain small data include existing information system flows within the organisation and these typically include the limited information flowing through Enterprise Resource Planning (ERP) Systems and Transport Management Systems (TMS). As adopted from the definition used in the field of Market Research, secondary data sources encompass the information that has

[1] Henceforth in this document, the use of "SCOR" will implicitly imply "SCOR®".

been generated by other organisations or scholars and can be adopted and used to extrapolate useful insight for decision-making (Andrei, 2018:94).

An example of such data is that supplied by economic research institutions such as the Bureau of Economic Research (BER). The institution publishes quarterly Consumer Confidence Indicators (CCI) data, which refers to the extent of consumer optimism about the state of the economy (McWhinney, 2018), as well as Business Confidence Index (BCI) data which is reflective of the sentiments across specific commercial industries (BER, 2022).

A review of literature demonstrates how the historical data of CCI can be used as input in forecasting models to predict the future state of associated variables. An example in manufacturing is where a low consumer confidence can be associated with a decline in customer spending, which could signal the need to decrease inventory in advance as sales are anticipated to decline and a decision to invest in new project or facilities may be deferred due to low CCI (Jain, 2014).

1.3 Data in Supply Chains

Big data offers new opportunities for retrieving the value from the large amounts of data that are constantly flowing in our supply chains (Curry, 2016:3). Big data refers to the enormous amount of data sets can no longer be processed by means of computers (Sanders, 2014). The analysis thereof, known as big data analytics (BDA), refers to the methodology that is used to analyse and derive value-adding insights from the large sets of data being examined (Sivarajah, Kamal, Irani and Weerakkody, 2017:265). Big data and BDA facilitate the improved efficiency and effectiveness of businesses (Wamba, Gunasekaran, Akter, Ren, Dubey and Childe, 2017:357). Figure 3 is a graphical description of the CPS, where the customer is the integrator between the physical supply chain and BDA and artificial intelligence.

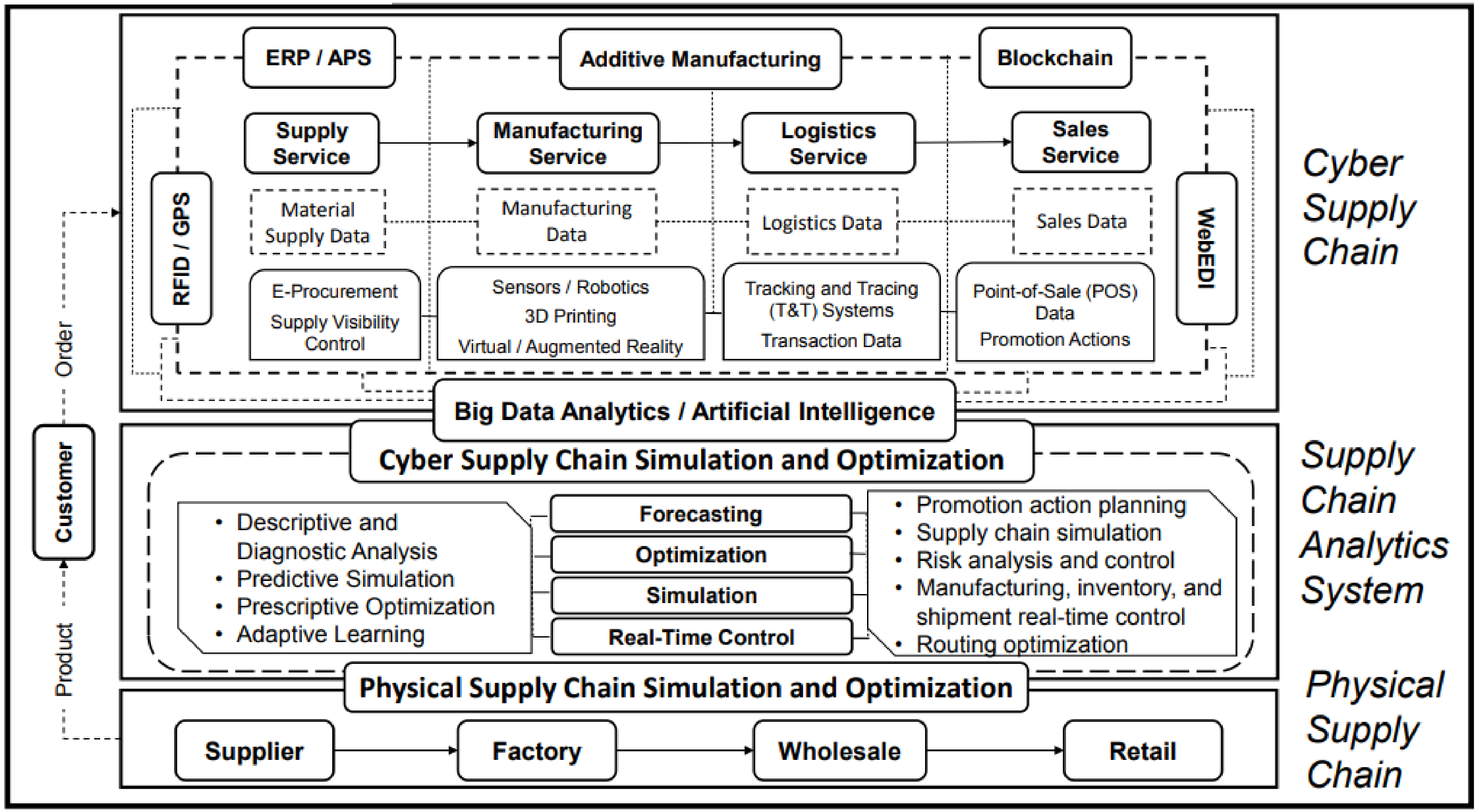

Figure 3: Service and material flow coordination in the cyber-physical supply chain (Ivanov *et al*., 2019:83).

Primary and secondary big data sources are defined similar to that of small data sources. Primary big data is found within the organisation and secondary big data is found external to the organisation. An example of primary big data sources in organisations is data that is extracted from sensors, typically connected to more than one computer device and can be viewed in real-time. Secondary big data includes data that is publicly available from databases such as social media ~~(Bekker, 2017).~~ (Cao, Schniederjans and Gu, 2021).

Related to the concepts of big data and BDA, is the application of business intelligence (BI) to supply chains. business intelligence comprises of two different definitions based on the use of the term "intelligence" (Babu, 2012:60). The first definition considers the analysis of business activities through human intelligence, and the second considers the application of technological intelligence systems and human cognitive faculties to support management decisions (Babu, 2012:60). Lönnqvist, and Pirttimäki, (2006:32) further define BI as a process which comprises of the acquisition, analysis and dissemination of information from both external and internal data sources that are relevant to business activities and decision-making processes. Chen, Chiang and Storey (2012, 1174) moreover define BDA as the BI technologies that are founded on the principles of statistical analysis and data mining. BI enables: the resolving of supply chain problems; the identification and leveraging of opportunities; and prediction and planning for operations and align operations to strategic business goals. Data warehousing is a critical enabler for BI and involves the Extraction, Transformation, and Loading (ETL) processes which combine data from various sources, validates, cleans, transforms, aggregates and loads into a data warehouse (Krmac, 2011), see Figure 4.

1.4 Supply Chain Analytics

The above-mentioned technological concepts and applications are used in Supply Chain Management (SCM) to support and enable the analysis of supply chains, known as supply chain analysis. Souza (2014:595) defines supply chain analytics (SCA) as an approach that makes use of information and analytics tools to make data-driven decisions about the flow of material and information within the supply chain. SCA models can be classified as descriptive, predictive and prescriptive analytics (Souza, 2014:595).

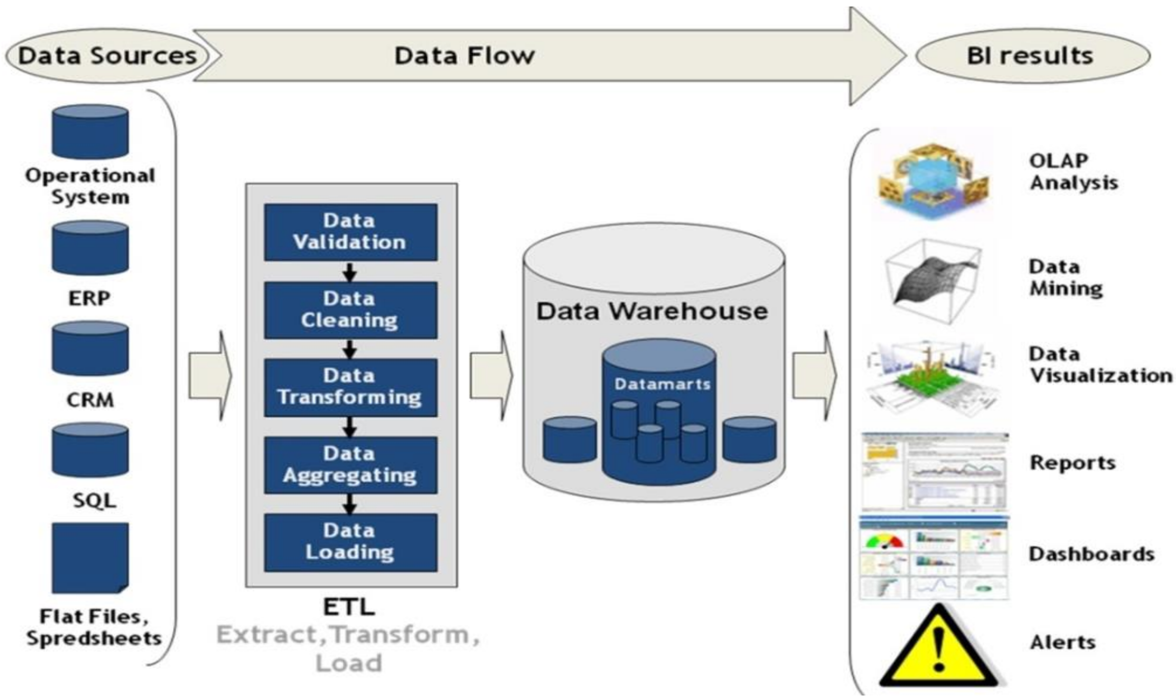

Figure 4: Extraction, Transformation, and Loading processes (Krmac, 2011).

Descriptive analytics makes use of information that is following through the supply chain and describes the current state of the supply chain (Souza, 2014:596). Predictive analytics, as defined by IBM (2019), aids organizations in performing business scenario analysis and identify the associated business implications of the respective scenarios. Souza (2015:596) highlights that the outcome of descriptive and prescriptive analytics serves as an input to prescriptive analytics which highlights the ideal state of the supply chain and its associated processes (2015:596). Chapter 3 provides a detailed discussion on SCA techniques and their application in supply chain processes.

Hahn and Packowski (2015: 45-52), as well as Souza (2014: 595-605) have respectively proposed ‘a framework for analytics applications in Supply Chain Management’ and an illustration of ‘analytic techniques used in Supply Chain Management’. Both research papers consider the applications of descriptive, predictive and prescriptive analytics applications in supply chain. Hahn and Packowski (2015:45-52) also consider other business aspects as well as Information Technology perspectives that they believe should form part of their analytics framework.

Among the investigations relating to supply chains analytics maturity is a paper by Arunachalam, Kumar and Kawalek (2018: 416-436) where they identify dimensions of BDA capabilities maturity that are essential to successful SCM, namely: data generation capability; data integration and management capabilities; advanced analytics capabilities; data visualization capabilities; and data-driven culture (Arunachalam *et al*., 2018:425-429). Gartner has also introduced a five-stage maturity model to for SCA (Bodenstab, 2017), which highlights the SCA maturity aspects as the business goals, data, and skills set of the practitioners, applications, data analytics techniques and the supporting technology used (Bodenstab, 2017).

The introduction of technological innovations has improved supply chain optimisation opportunities and it has also introduced some new challenges, while the integration of systems for data mining, analytic applications and business intelligence has improved over the years (Kohavi, Rothleder and Simoudis, 2002:45-48). Most of the existing literature focuses on identifying methods in which analytics and business intelligence can be used to derive value from supply chain data and enhance supply chain performance. However, there exists a gap between the use of analytics tools and the ability of the users to extract information from them as per strategic business needs (Kohavi *et al*., 2002). Chae, Yang, Olson, and Sheu, (2014:3) further supported the view that SCA research is in its infancy stages and there is a general absence substantial theory and of empirical studies. A detailed discussion of SCA can be found in Chapter 3 of the thesis.

Contemporary supply chain literature links resilience of the DSC to the analysis of data. Supply chain resilience (SCR) defines the capability of organisation to operate during disturbances and disruptions while experiencing minimal to none impact on their supply chain performance (Donadoni, *et.al.*, 2019)~~Scholten, Stevenson and van Donk, 2019:1~~). As a result, organisations must pay attention to the conception of supply chain resilience and investigate strategies to develop this attribute. Supply chain risk managers look to simulation and optimisation models to support their decision-making. These models use historical data to reconstruct disruption scenarios and real-time data to anticipate emerging disruptions, as well as deploy recovery policies (Ivanov and Dolgui, 2021). Technological innovation and data analytics have therefore become a budding topic from the perspective of supply chain resilience (Iftikhar, Ali, Arslan, and Tarba, 2022).

1.5 Supply Chain Risks

Technology has allowed organisations to operate their supply chains beyond their boarder to acquire cheaper materials and services. Global supply chains are characterised by organisations that either distribute their products across international borders, have facilities in other countries or source supplies from other countries (Koberg and Longoni, 2019:1084). The networks comprise of both Business-to-Business (B2B) and Business-to-Customer (B2C) transactions, which ultimately translates to links between the global supply chain, local supply chains and customers, as illustrated by Figure 5. According to Ivanov and Dolgui (2020: 2907), the nature of these Intertwined Supply Networks (ISN) is such that firms play the roles of both competitors and suppliers within the same supply chain network.

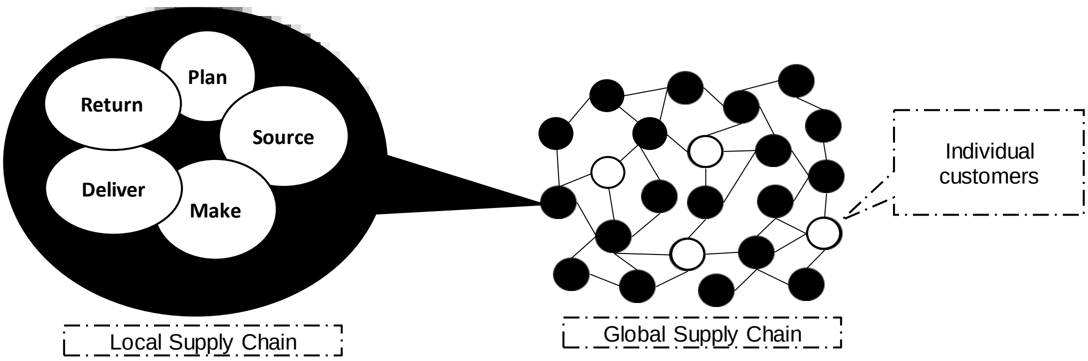

Figure 5: The interconnected global supply chain, local supply chains and customers.

The COVID-19 pandemic has however introduced disruptions across the global supply chain and has altered the way we view supply chain resilience. Post pandemic trends in global supply chains include: logistics disruption, where the flow of import and export goods has been restricted by the shutdown of major global ports and in response to this, governments and private companies are exploring strategies to improve resilience and boost domestic capabilities; production delays, where the limited supply of key commodities and logistical capacity has led to stock unavailability of products and long purchase lead times; over reliance on a limited number of third parties; technology investment, where investment in critical supply chain planning capabilities and the adaptation of advanced digital enabler such as predictive analytics to improve supply chain visibility and improve supply chain responsiveness to disruptions; and commodity pricing, where organisations are focusing on digital transformation and technology to enable the seamless flow of information across their supply chains by leveraging spend analytics tools. Increased technology investment plays a critical role in improved supply chain efficiency and resilience (KPMG, 2022).

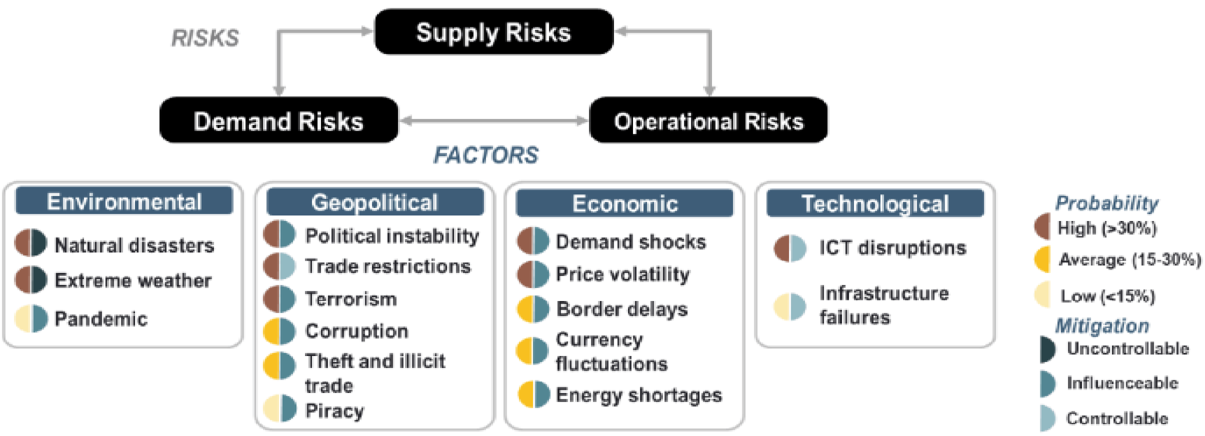

Figure 6: Global Supply Chain Risks (Rodrigue, 2020).

The overall risks associated with global supply chains can be categorised as supply, demand and operations risks and these are influenced by factors that span across environmental, geopolitical, economic and technological spectrums which vary in probability of occurrence (Rodrigue, 2020), as depicted in Figure 6. Supply chain planning practices that do not address demand variations, when not addressed appropriately, may result in loss of market share and reduced customer service levels (Jabbarzadeh,Fahimnia and Sheu, 2017:620). Similarly, supply variations also pose a supply chain risk as customers may resort to alternative suppliers (Tang, Gurnani and Gupta, 2014:1198).

Extreme weather conditions such as heatwaves, floods and droughts are the exposition of climate change. The costs associated with such events have considerably increased over the years and poses a threat to the global supply chain (Ghadge, Wurtmann and Seuring, 2020). Global politics has also shared its view on climate change, 196 countries partaking in the Paris Climate Agreement in 2015 which was enforced on 4 November 2015 (United Nations Framework Convention on Climate Change, 2022). Implications of this agreement entails the commitment to decrease carbon emissions by the relevant nations, which will ultimately impact regulatory policies that may restrict the trade of organisations who do not adhere to these policies.

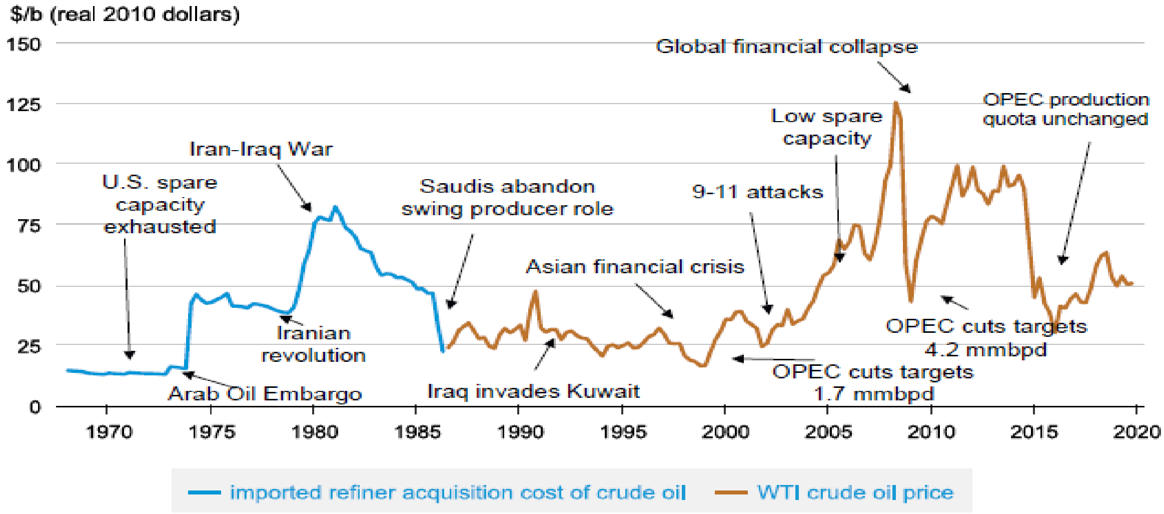

Figure 7: WTI crude oil prices vis-à-vis a variety of geopolitical and economic events (EIA, 2020).

Another key factor that affects supply chain is that of geopolitical risks. Geopolitical risks are defined as "… *the risk associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations*", (Caldara and Iacoviello, 2018). Figure 7 summarises impacts of major geopolitical events that have imposed a form of supply chain risk using the price of West Texas Intermediate (WTI) crude oil price as a proxy.

Crude oil supply chain dynamics are central to the flow of goods and services across the supply chain, and the security of energy supply therefore plays a pivotal role in the global supply chain. Energy security refers to the affordable and uninterrupted availability of energy sources and comprises of two aspects: the first aspect focusses on the long-term energy security which focuses on timely investments to supply energy as per economic developments; and the second is of short-term focus, where the ability of the energy system to react swiftly to sudden changes in supply-demand balance (International Energy Agency, 2022). The 2020 COVID-19 pandemic outbreak has had the most detrimental impact on crude oil prices compared to previous global recessions. Mitigation measures during the pandemic, such as the closing of international boarders, have had an adverse impact on all commodity markets, with crude oil being impacted the most (Baffes and Nagle, 2020). Changing consumer patterns, including the decline of discretionary spending and job losses because of the pandemic, have also contributed to the sharp falls in the global markets (Fernandes, 2020:2).

In summary, SCM has metamorphosised into a DSC network that is underpinned by technologies such as IoT and CPS. These networks are demand driven and are constantly generating data of which the most powerful of this is customer data. Analysis of such data, referred to herein as SCA, provides supply chain insight and informs strategic decision-making. However, there exists a gap between the use of analytics and the ability of practitioners to extract information from them.

Second, micro- and macro-economic pressures of the global supply chain are altering the nature of local DSC networks and are inciting deglobalisation. Parallel to this development, crude oil prices drive the flow of goods through the supply chain to meet customer demand. The prediction of petroleum products is therefore key to ensure supply security and inform policy.

1.6 Overarching Research Question

The overarching research question of this thesis is as follows:

> *What are the capabilities that are necessary to perform effective supply chain analytics using customer data?*

1.7 Contributions

The contribution made in this thesis is two folds. This research proposes a theoretical framework for linking customer data to supply chains; and predictive models for petrol and diesel consumption (growth%) are developed where both domestic and international independent variables are tested in the model.

1.8 Justification for the Research

The interconnectedness of global supply chains has necessitated the need for organisations to embed supply chain resilience within their supply chain processes. To develop the appropriate supply chain strategy and policy, organisations need to address the following gaps:

i) Existing literature links demand analysis to advanced analytics capabilities in supply chains through application specific research, for example, focusing on data-driven approaches to demand forecasting (Pereira and Frazzon, 2021). There is however a low uptake of the advanced analytics approach by organisations due to the lack of understanding of how it can be implemented, as well as the incapability to identify appropriate data to be harvested (Nguyen *et al*., 2018). This challenge is further aggravated by the limited research that integrates the digital and physical worlds within supply chains (Pereira and Frazzon, 2021). A review of literature suggests that the missing integrant in contemporary supply chain strategy is the ability to recognise the relationships between consumer behaviour and supply chain design and management.

ii) While technology has virtually linked the global supply chain landscape, it is the price of oil that has incited a trend towards deglobalisation (Iqbal, 2022). It is evident that the impact of crude oil price changes spans from impact on family budgets, to the earning by corporate companies, to the Gross Domestic Product (GDP) of countries (Bajpai, 2020). It is therefore necessary to predict oil product consumption in order to appropriately mitigate supply chain risks, anticipate consumer demand and recommend appropriate policy.

1.9 Outline of Thesis

In Chapter 2, a literature review of the evolution of the SCOR model parallel to the industrial revolutions is conducted and the relevance of the SCOR model in the contemporary supply chain is demonstrated. Chapter 3 presents a set of proposed capabilities for linking customer data to the supply chain. A case-study approach is adopted, whereby employees from a petroleum company were approached to participate in a web-based survey. A set of hypotheses were proposed to test the set of capabilities that were derived from literature using Structured Equation Models (SEM). Confirmatory Factor Analysis (CFA) is also used to test the strength of the relationships between observed and latent variables. In Chapter 4 we use simple linear regression to test the predictive significance of CCI and BCI to the consumption of South Africa's petrol and diesel consumption (growth%) and multiple linear regression is used to test the predictive significance of CCI and BCI respectively in conjunction with GDP, Brent crude price (ZAR) and GSCPI. Finally, the conclusions and implications of the thesis are discussed in Chapter 5.

1.10 Delimitations of Scope and Key Assumptions

In Chapter 3 a single-case design study approach is used, and the respondents of the survey are from a multinational petrochemicals company whose head offices are based in South Africa. The results of the survey conducted are therefore limited to the experiences of the respondents within the organisation. Additionally, in Chapter 4, the predictor variables considered are limited to CCI, BCI, GDP, Brent crude price (ZAR) and GSCPI, with the assumption that they are the primary drivers of petrol and diesel consumption in South Africa.

1.11 Conclusion

The discussions in this thesis aim to develop a proposed framework for SCA using customer data using both qualitative and quantitative approaches. The thesis explores how customer data can be integrated into the supply chain processes in the context of: (i) traditional supply chain approaches; (ii) a proposed set of contemporary capabilities are proposed; and (iii) the predictive significance of predefined predictor variables for the consumption of South Africa's petrol and diesel is completed using simple and multiple linear regression. The insights derived from each chapter are intended to contribute towards the overall understanding and development of a framework for SCA using customer data for the prediction of petrol and diesel consumption in South Africa.

2 THE SUPPLY CHAIN OPERATIONS REFERENCE MODEL

The most widely recognised supply chain model, or framework, is the SCOR model (Theeranuphattana and Tang, 2008:126). The SCOR model was originally developed in 1996 and is now endorsed by the Supply Chain Council (SCC), which was founded by a consulting company called Pittiglio, Rabin, Todd and McGrath (PRTM). The objective was to standardise supply chain processes and to create measures against which supply chain performance can be tracked or benchmarked (White, 2018).

Persson (2011:288) defines the SCOR model as a guideline to the mapping, benchmarking and improvement of supply chain operations. Other noted outputs of the model are in its ability to link supply chain business process, performance metrics, best practices and technologies into an integrated structure that supports communication among supply chain stakeholders and seeks to increase the effectiveness of SCM and related supply chain improvement activities (APICS, 2019). The SCC merged with the American Production and Inventory Control Society (APICS) in the year 2015 and have since published later versions of the SCOR model.

The business process activities which are linked to satisfying customer demand as defined by the SCOR model (APICS, 2019) in Figure 8. The SCOR model highlights that every basic supply chain comprises of five components namely: *Plan, Source, Make, Deliver* and *Return* functions, and that these activities are all linked (Huan, Sheoran and Wang, 2004:24) as follows:

- *Plan* processes are associated with planning activities of supply chain operations (SCC, 2019:12) which include the gathering of customer demands; the collection of information of resources being utilised in the supply chain; balancing customer demands to resource capabilities and subsequently identifying any gaps (SCC, 2019:12).

Figure 8: Supply Chain Operations Reference (SCOR) Model Ntabe, Lebel, Munson and Santa-Eulalia (2015).

- *Source* processes include the schedule development and ordering of goods and services of the specific supply chain (SCC, 2019:12).
- *Make* process of the SCOR model describe supply chain activities that are executed to convert sourced materials or are performed to create content for services (SCC, 2019:12).
- *Deliver* processes comprises of activities associated with the fulfilment and maintenance of customer orders (SCC, 2019:12).
- *Return* processes which are associated with the reverse flow of goods from the customer (SCC, 2019:12).

The SCOR model is comprised of three hierarchical levels as illustrated in Table 1 (APICS, 2017: 11). Levels 1 and 2 provide standard supply chain architecture process and level 3 describes the implementation of the architecture APICS, 2017: 11). SCOR related literature published between the years of 2000 to 2005 focused mainly on the applications of the SCOR model, either in isolation, or in combination with other methodologies such as Lean Manufacturing and Six Sigma (Swartwood, 2003:1-4). Lean Manufacturing methods aim to reduce process cycle time by eliminating process deficiencies, while the Six Sigma methodology is applied to improve the quality of process outputs by reducing process variation (Swartwood, 2003:1). During this era, authors were attentive to the topics of defining SCOR, its associated metrics and how it can be applied in practice (Bolstorff (2001); Bolstorff (2002:22-25); Bolstorff and Rosenbaum (2003)).

Table 1: SCOR process levels (SCC. 2019: 11).

	Level	Application	Examples
In Scope Applicable Across Industries	**1**	Level 1 processes are used to describe the scope and high-level configuration of a supply chain. SCOR has five level 1 processes.	Plan, Source, Make, Deliver, and Return
	2	Level 2 processes differentiate the strategies of the level 1 processes. Both the level 2 processes themselves as well as their positioning in the supply chain determine the supply chain strategy. SCOR contains 26 level 2 processes.	Example Make level 2 processes: › Make-to-Stock › Make-to-Order › Engineer-to-Order
	3	Level 3 processes describe the steps performed to execute the level 2 processes. The sequence in which these processes are executed influences the performance of the level 2 processes and the overall supply chain. SCOR contains 185 level 3 processes.	Example Make-to-Order level 3 processes: › Schedule Production Activities › Issue Product › Dispose Waste › Release Product
Not in Scope Industry Specific	**4**	Level 4 processes describe the industry specific activities required to perform level 3 processes. Level 4 processes describe the detailed implementation of a process. SCOR does not detail level 4 processes. Organizations and industries develop their own level 4 processes.	Example › Print Pick List › Pick Items (Bin) › Deliver Bin to Production Cell › Return Empty Bins to Pick Area › Close Pick Order

The evolution of the SCOR model has been highly driven by technological advancements that impact supply chain processes. One of the most important supply chain technologies that received attention since its inception, is the Enterprise Resource Planning (ERP) system. The integration of supply chains through ERP systems gained interest since the late 1980s (Themistocleous, Irani and Love, 2002:1088), and the ERP software enabled the integration of company data throughout the organisation (Davenport, 1998:122). Davenport (1998:122) highlights that, in parallel to the rise of the internet, the adaptation of ERP by organisations may have been the most notable use of information technology by corporates in the 1990s.

Another effective development was the integration of the SCOR model within the ERP environment in supply chain using the RFID (Radio Frequency Identification) tag technology, that is, technology that makes use of radio signals to transmit data about the location of whichever item the tag or smart card it is attached to (Savino, Menanno, Chen and Ragno, 2018:1-7). To summarise the study by Savino *et al*. (2018:1-7), the authors proposed an integrated approach for a SCOR-based model approach in an ERP system enabled environment that also makes use of RFID technology.

2.1 Brief Overview of the Industrial Revolutions

Emerging technologies have altered business models and changed the end-to-end view of supply chains over the centuries. More (2002:3) defines an Industrial Revolution (IR) as an implied growth in industrialisation and elaborates that, in the 4IR context, industrialisation refers to commerce functions such as mining, manufacturing, as well as construction. Hudson (2014:6) suggests that some of the factors that influence the rise of an industrial revolution include: the rate of increase in the net capital accumulation for a country; the increased ability to trade worldwide; technological innovations, as well as the increase of goods and services as a result of increased populations. Industrialisation encompasses of a growth in an industry and its related sectors in the economy (More, 2002:3). In the lead up to the 4IR, there has been four industrial revolutions so far.

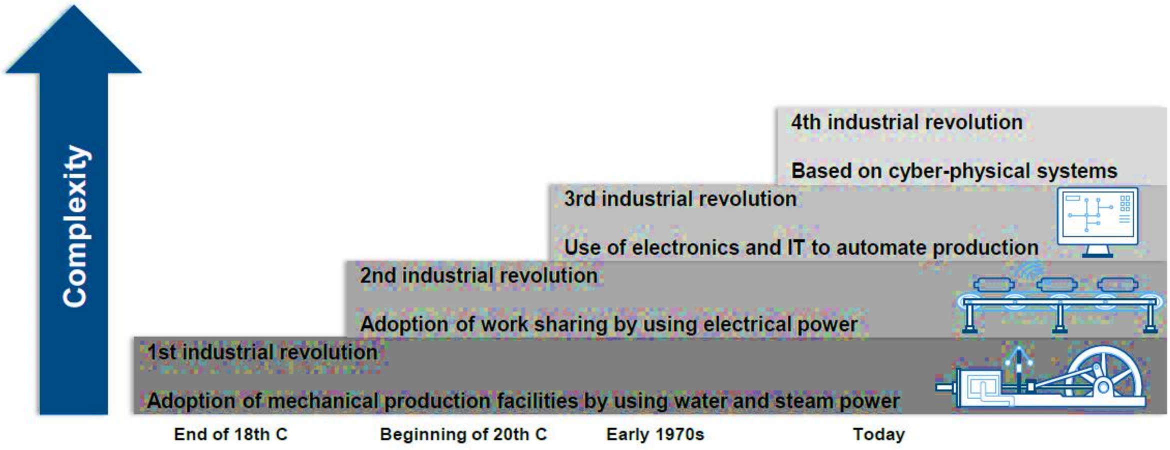

Figure 9: The industrial revolutions (Van Herreweghe, 2015).

The First Industrial Revolution originated in Great Britain (Chen, 2019) and was characterised by the mechanization of the textile industry (Magal, 2019). The revolution spanned the period between 1760 to 1840 with the discovered use of steam to serve as a source of energy for machinery, and paved the way for various inventions (Vyas, 2018), impacting numerous industries and the mining sector (Clark, 2007:7). The manufacturing of textiles and the rail transportation system were particularly influenced by this industrialisation (Supply Chain Game Changer ™, 2020).

The Second Industrial Revolution flourished during the period between 1850-1970 and began in America (Vale (2016), Chen (2019)), and characterised using electrical energy to enable mass production and the assembly-line concept (Van Herreweghe, 2015:2). This era also marked the completion of the world's first transcontinental railroad (Chen, 2019). The Second Industrial Revolution was also referred to by some historians as the "The Technological Revolution" (Supply Chain Game Changer™, 2020).

The Third Industrial Revolution was driven by the extensive use of digitalisation methods (Lasi, Fettke, Kemper, Feld and Hoffmann, 2014:239). Pouspourika (2019) highlights that this revolution began in 1969 and enabled the efficient use of electronics, telecommunication devices and the computers and consequently, increased the cost efficiency of digital manufacturing practices and commerce enabled by the internet (Troxler, 2013:2). Some of the noteworthy technological innovations of the Third Industrial Revolution include the creation of the first intelligent humanoid robot that was developed in 1972 in Japan and the inception of the Google search engine in 1998 (Magal, 2019). The significance of the third Industrial Revolution can be indicative from the observation of Dosi, Galambos and Orsanigo (2013:2) who noted that a Google search of “the third industrial revolution” yields more than 150 million entries.

The Fourth Industrial Revolution started at the end of the 18th century, sometimes referred to as Industry 4.0, is characterised by technologies such as advanced robotics and autonomous systems (WEF, 2017:4). In its report, the WEF (2017:4) noted the unparalleled degree and rate at which contemporary global supply chains are being altered as a result of the Fourth Industrial Revolution (4IR). Although the Industry 4.0 concept is believed to have begun in Germany (Rojko, 2017). Tjahjono, Esplugues, Ares, and Pelaez (2017: 1176) are of the view that this concept is bares similarities to technological developments that occurred in other European countries.

2.2 The Future of The SCOR Model in the Age of 4IR

The SCOR model has not been without its flaws, Hwang, Han, Jun and Park (2014:6) cited one of the shortfalls of the SCOR model as the process of reviewing the various proposed supply chain metrics. The authors were of the view that having to select the appropriate metrics and monitor these for a supply chain is rather tedious. Another shortfall of the SCOR model is derived from the implications of a study performed by Lockamy and McCormack (2004:1210) in which the authors investigated the relationship between SCM planning practices and supply chain performance based on the SCOR model processes, which they defined as key decision areas. In their findings, Lockamy and McCormack (2004:1210) insinuate that the application of best practice models such as SCOR do not necessarily provide the same perceived supply chain performance benefits in every supply chain.

Although shortfalls of SCOR as highlighted by literature are noted, the SCOR is still able to serve as a foundation for assessing DSC. Deloitte and The Association for Supply Chain Management (ASCM) have in recent months announced their first publication of the Digital Capabilities Model (DCM) for Supply Networks (Deloitte, 2019). The purpose of the DCM for supply networks is to model the development of DSC networks, and further highlights that the objective of the model is to assist organisations in understanding their digital supply networks and the maturity of their processes (Deloitte, 2019). Companies that are already using the SCOR model only need to map each DCM capability to the relevant aspects of the SCOR Digital Standard (Deloitte, 2019). However, DCM remains to be widely adopted by organisations because they generally resort to business analysis techniques such as business process re-engineering and SCA. The combination of business analysis techniques and SCA facilitates the interpretation of data that is flowing in the supply chain because of the existing understanding of these methodologies.

Based on the literature review discussed, it is evident that there exists opportunity for the SCOR model to be further refined and be adapted and adopted to accommodate technological advances within the supply chain environment. Millet, Schmitt and Botta-Genoulaz (2009:406) performed a critical analysis of the SCOR model and assessed its contribution to the integration of both business processes and information systems. In their study, the authors saw it fit to propose a SCOR-based reference model that would extend upon the SCOR reference model (Millet *et al*., 2009:406). The authors argued that the SCOR model only enables the configuration of process maps based physical product flows and does not facilitate the flow of information within the supply chain (Millet *et al*., 2009:404).

The SCOR model has served as a guideline for supply chain processes and best practices for years. The landscape of supply chains has evolved due to technological innovations, and this has subsequently led to a need for a supply chain framework that will address processes associated with the DSC. As cited by Deloitte (2019), the DCM for supply networks is the initial attempt of the supply chain community in addressing this shortfall of the SCOR model. The SCOR model, none the less, will remain to be the mostly widely recognised supply chain framework (Theeranuphattana and Tang, 2008:126).

2.3 Is the SCOR Model still Relevant?

The need for a structured approach to the contemporary supply chain and its associated risks in each level and process is not only necessary, but also urgent. The emerging supply chain landscape is one that is highly characterised and influenced by disruptive technologies. It is thus important to define the characteristics of this new landscape and question whether traditional frameworks, such as the SCOR model, can still be used as a foundation to address the emerging challenges of DSC networks.

Changes to the SCOR model are instituted as and when deemed necessary by the SCC in response to changes in the supply chain environment (Poluha, 2007:60). In Version 4.0 of the model, performance attributes were introduced, and process descriptions were also adjusted to reflect the defined process metrics to the appropriate supply chain object (Poluha, 2007:58). Versions 5.0 and 6.0 saw the inclusion of additional supply chain processes, specifically, the *Return* process and the incorporation of processes related to retail, return and electronic business respectively (Lockamy and McCormack (2004:1192); Poluha (2007:60)). Published in 2015, Version 7.0 included two changes, namely, the simplification of performance indicators and the addition of new procedures to supply chain best practices. The fundamental revisions of Version 8.0 focused in the areas of performance indicators, best practices, and a system view of the supply chain database (Poluha, 2007:61). Version 9.0 of the SCOR model finally expanded to include risk management capabilities (BusinessWire, 2008). While Versions 10.0 and 11.0 introduced a section addressing People Skills in supply chains and the introduction of the “Cost to Serve” metric respectively (APICS (2019); SCC (2012)). To answer the question of the relevance of the SCOR model in the contemporary supply chain, one must retrospectively analyse the fall of the model subsequent to it adaptation and its resilience thereafter.

The latest version of the SCOR model is SCOR 12.0 (APICS, 2017). According to APICS (2020), the SCOR model has been updated to address several drivers of supply chain success in the current supply chain environment. These include today’s supply chain technology such as blockchain technology (APICS, 2020). Blockchain technology is defined as a digital distribution ledger of transactions that cannot be altered as result of cryptographic methods (Hackius and Petersen, 2017:5), to ensure that information that is shared is not compromised. In addition to blockchain technology, SCOR 12.0 aims to enable DSC strategies of organisations by presenting modernised best practices and processes. It should be noted, that this recent SCOR model, in its discussion, states that the model does not dictate how an organisation should execute its functions, nor does it dictate the tailoring of its information/system flows (APICS, 2017).

The introduction of advanced technologies has however altered the view of traditional supply chains. While the traditional supply chain comprises of physical locations that are linked through transportation lines, contemporary supply chain is one of a digital nature (Büyüközkan and Göçer, 2018:157). The growing adaptation of digital technologies in societies, together with their associated changes in the way in which individuals connect and behave is referred to as digitalisation (Agrawal and Narain, 2018:2). The resulting dynamic set of supply networks that have emerged as a result of the 4IR, are known as a DSC network (Deloitte©, 2016:7 - 8).

According to Korpela, Hallikas and Dahlberg (2017:4183), DSC improve the communication between organisations that are part of this supply chain network through the strategic and operative exchange of information. The inter-organisational links within the DSC enable the linking of information systems between the actors from the point of sourcing until when the product or service is supplied to the customer (Korpela *et al*., 2017:4183). The adaptation of 4IR technologies in supply chains has resulted in an increase of information that flows through the supply chain.

As practitioners and scholars are gaining knowledge about the DSCs, we see emerging trends in the contemporary SCM landscape. Digital Supply Chain Management (DSCM) is one of those emerging trends, which in simple terms, refers to the management of supply chains that have adopted technologies in their operations (Johnson, 2019). Other trends include opportunities which have been present to organisations to expand their supply chain networks into previously neglected regions, and we see this in third world countries such as

South Africa. Case in point is the investment made by South African municipalities who are reported to have spent on infrastructure that intends to provide free Wi-Fi connection to its township residents (Rogerson, 2019) ~~(Mahlangu, 2019)~~. Furthermore, the competition of supply chains has also been accentuated by increased customer expectations and the growing trend towards the individualisation and customisation of products and services (McKinsey, 2020). The mass customisation campaign by the German sports brand Adidas demonstrates this point well, when back in 2017 the brand launch a campaign that allowed their customers to order and customise products to their liking, which were delivered within the cycle time of four hours (Sparrow, 2017)~~(Connelly, 2019)~~. While the inherent nature of contemporary supply chain landscape may require organisations to think creatively and use technology in an innovative manner.

2.4 Re-Designing the Future of Supply Chains Post-Pandemic

The foundations of SCM that are presented by the SCOR model are still relevant in contemporary supply chains and as such, this thesis asserts that future attempts to construct a novel SCM framework should be based on the learnings of and from the SCOR model. The construction of a novel SCM framework needs to appreciate that the neoteric supply chain landscape comprises of global supply chains and that these are complex, and comprise of various organisations that work together and may be based in separate geographical locations (Short *et al*., 2016:1085).

Supply Chain Risk Management (SCRM) is necessary for every supply chain, regardless of whether it is integrated or independent. Thus, global supply chains are naturally vulnerable to disruptions caused by both natural as well as human-made disasters (Jabbarzadeh *et al*., 2018:5945). The history of SCM includes various attempts by scholars to use the SCOR model as a foundation to propose various Supply Chain Resilience Management (SCRM) approaches. Among the previously proposed methodologies is the recommended use of the SCOR standard performance metrics to identify potential risk factors and their perceived level of influence in supply chain operations (Ríos *et al*., 2019:2-20). Other cited uses of the SCOR model as a SCRM tool include: the identification of internal and supply chain wide risk management strategies; the combination of SCRM with other management disciplines such as Security Management, as well as, the use of SCOR processes as an input to the development of proposed SCRM tools (Brandt *et al*., 2019:125).

Earlier applications of SCOR to SCRM have been rather manual and are not adoptive to technology-enabled supply chains. In contrast, modern supply chains are enabled to address risks by making use of intelligent systems, that are enabled by digitalised supply chain processes to respond to disruptions in a timely manner, referred to as smart-SCRM (Schlüter *et al*., 2019:179-206). It is paramount to note that not all organisations are enabled to invest in automated risk response systems, particularly those operating in developing world countries, and thus, traditional SCM frameworks are still prevalent in facilitating the response of supply chains in the face of disruptions. Factors that influence the adaptation of 4IR applications in these countries include, among others, the shortage of skills in the fields of science, technology, engineering and mathematics, as well as, sluggish job creation within these economies (Sutherland, 2020:233-252). While the COVID-19 pandemic has altered and disrupted global supply chains, the performance domains of the SCOR model are still relevant in guiding the required rapid response to the pandemic.

2.5 Designing for Supply Chain Reliability Post-Pandemic

The COVID-19 pandemic has resulted in the disruption of material flow throughout the global supply chain. Worldwide, countries had closed their boarders to curb the rate of COVID-19 infections and for countries that source their raw materials and products internationally, this subsequently meant supply shocks to their supply chains. Order fulfilment, which is reflective of supply chain reliability, was one of the significantly impacted supply chain aspects as disruptions in supply chain processes subsequently meant that products could not reach consumers, and this ultimately resulted in lost profits. While various supply chains have seen a significant decrease in demand for their goods and services, food and medical supply chains experienced a surge in demand (Seifert and Markoff, 2020).

Electronic Data Interchange (EDI), as identified by SCOR, is as a best practice approach which implies automated transactions into vendor data bases, as well as their ordering systems (SCC, 2012). DSC networks facilitate EDI transactions through blockchain technology, also referred to as extreme automation (Fiaidhi *et al*., 2018). The cited benefits of EDI include supply chain cost and time reduction and improved customer satisfaction as supply chain lead time are ultimately reduced. The Africa Medical Supplies Platform (AMSP) provides an ideal example of how the medical supply chain has reconfigured Africa's medical supply chain to achieve reliability through such a system. The online marketplace provides access to African Union Member States to vetted manufacturers and procurement strategic partners (Tralac, 2020). A prerequisite of such a strategy does of course require significant investment in Information Communication and Technology (ICT) infrastructure by the supply chain actors. The pandemic demonstrated the importance of technology in the current supply chain landscape and has made the case for previously resistant or sluggish adopters to adopt new technologies, or risk extinction. Organisations now need to establish a culture where new technologies are constantly explored and embraced (Laluyaux, 2020).

Demand planning and forecast provides an anticipated outlook on customer demand with the input of various stakeholders, including suppliers and supply chain planners, and makes use of customer data (SCC,2012). An immense opportunity to enhance demand planning lies in the use of secondary data sources that have proven to be useful in the development of forecasting models. Google Trends, for example, is a type of online big data that is representative of public sentiments. The trends provide unfiltered data samples, and its results are representative of all Google search queries within a specified timeframe, and the data is also normalised according to time and location of query and the results are scaled between 0 and 100 (Google, 2020). The value of Google Trends has become apparent over the years, and this has led to the application of online big data being used in several industries (Jun *et al*., 2018:85).

2.6 Designing for Supply Chain Agility and Responsiveness Post-Pandemic

The COVID-19 pandemic has brought about a shift in the needs of consumers and has consequently rendered the strategic focus of some supply chains obsolete while asserting pressure on others. Demonstrating agility and responsiveness, automotive manufacturers experienced a sharp fall in car sales during the pandemic and responded by repurposing their manufacturing plants for the production valves for respirators in response to the increased demand for these (Ivanov and Dolgui, 2020). Additionally, various manufacturers of fragrances have also repurposed their factories to produce alcohol-based sanitizers. Moreover, there was an increase of e-commerce activities and logistics services enabled by mobile technology (Khan *et al*., 2020).

Supply chain network planning is a SCOR best practice that enables responsiveness (SCC, 2012) and is achieved through the application of SCA techniques to test scenarios in a virtual supply chain environment. For organisations who have not already done so, there is a need for the investment in supply chain technology to facilitate agility and responsiveness (Accenture, 2020). The visualisation of material movement across the supply network enables the understanding of the physical material movements and this ultimately yields insight for decisions that result in supply chain resilience (Golan *et al*., 2020). The resulting DSC networks are expected to facilitate this process by providing real-time data that will enable supply chain planners to make data-driven decisions, as this will result in agile and responsive supply chains. Even though the DSC network has a vast amount of technology to develop advanced forecast models, some disruptive events can unfortunately not be foreseen, and it is therefore imperative to incorporate agility in the design of supply chains. An agile supply chain is one that can proactively anticipate disruption and is prepared for sudden changes that impact the *Plan, Source, Make, Deliver, Return* and *Enable* processes (SCC). We have witnessed the consequences of an integrated nature of global supply chains which does not however justify anti-globalism, instead it calls for the dual sourcing from multiple countries to alleviate the excess dependency on countries like China (Baldwin and Tomiura, 2020:69).

An agile supply chain strategy is one that seeks ways in which flexibility can be incorporated into their business processes. As such, it is anticipated that in manufacturing, for example, organisations will move towards a China+1 strategy (Hedwall, 2020), which implies that sourcing options will not be limited to only China, instead, organisations will invest in alternative sourcing strategies, and this approach of course has additional cost implications. One might argue that in this example the substitution for China is not so simple as 60% of global consumer goods exports are accounted for by the country (Hedwall, 2020). Nevertheless, the aftermath of the global supply chain disruption presents an opportunity for other countries to attract international business by investing in their manufacturing capabilities, and coupled attractive offerings for land, labour, and logistics.

2.7 Designing for Supply Chain Asset Management Post-Pandemic

SCOR11.0 highlights that SCRM applications to Asset Management should reduce inventory variability. To achieve this during times of demand uncertainty, organisations are to leverage insights obtained from data to inform their inventory models. The SCOR model identifies collaborative inventory planning as a best practice that is intended to include key customers in the planning process. The metrics in this sphere include return on working capital, supply chain revenue and forecasting. Return on working capital assesses the amount of investment relative to the organisation's working capital versus the supply chain revenue. Supply chain revenue on the other hand refers to the revenue generated through supply chain operations (SCC, 2012).

Asset management optimisation post the pandemic should focus on generating optimal value from the organisation's assets and to achieve this, organisations are to enhance their supply chain capabilities across their networks. This would of course require investment on infrastructure by organisations and the countries within which they operate in. The investment by countries in their own capabilities also implies that local firms would get an opportunity to shift their strategic sourcing processes from international markets to local sourcing, thus reducing supply lead time and Cost of Goods Sold (COGS).

The post-COVID19 supply chain landscape will require such a collaborative integrated planning to be merged with SCA practices to achieve the organisational targets in these performance areas. While the initial total cost to serve will initially increase, the prospect of a resilient supply chain is enough motivation for this trade-off.

While traditional frameworks such as SCOR provide a foundation for supply chain optimisation, a novel approach to managing the emerging customer-driven supply chain is required. Traditional supply chains are being transformed into demand sensitive digital networks (Agrawal and Narain, 2018). The missing integrant in contemporary supply chain strategy is the ability to recognise the relationships between consumer behaviour and supply chain design and management (Gattorna, and Jones,1998:1).

The digitalised supply chain is constantly generating data at each point of the supply chain processes, namely, *Plan, Make, Source, Deliver* and *Return.* Customer experience and satisfaction is an indicator of how efficiently and effectively the information flows across supply chain activities. A Customer Relationship Management approach to establishing capabilities that are necessary to successfully apply SCA techniques is proposed in this thesis. In Chapter 3 of the thesis the proposed integration that provides the missing link between customer data and supply chains is presented.

3 LINKING CUSTOMER DATA TO THE SUPPLY CHAIN

This thesis adopts the view of Biswas and Sen (2016) who suggest that in a data-driven supply chain structure, demand is initiated by customer needs, and flows through successive stages to the supplier end. In this thesis the data is broadly classified as being generated at the various supply chain nodes as supplier, manufacturing, distribution, and customer data. Figure 10 and Table 2 illustrate a data driven general supply chain structure and the types of data generated at different nodes of a supply chain, respectively.

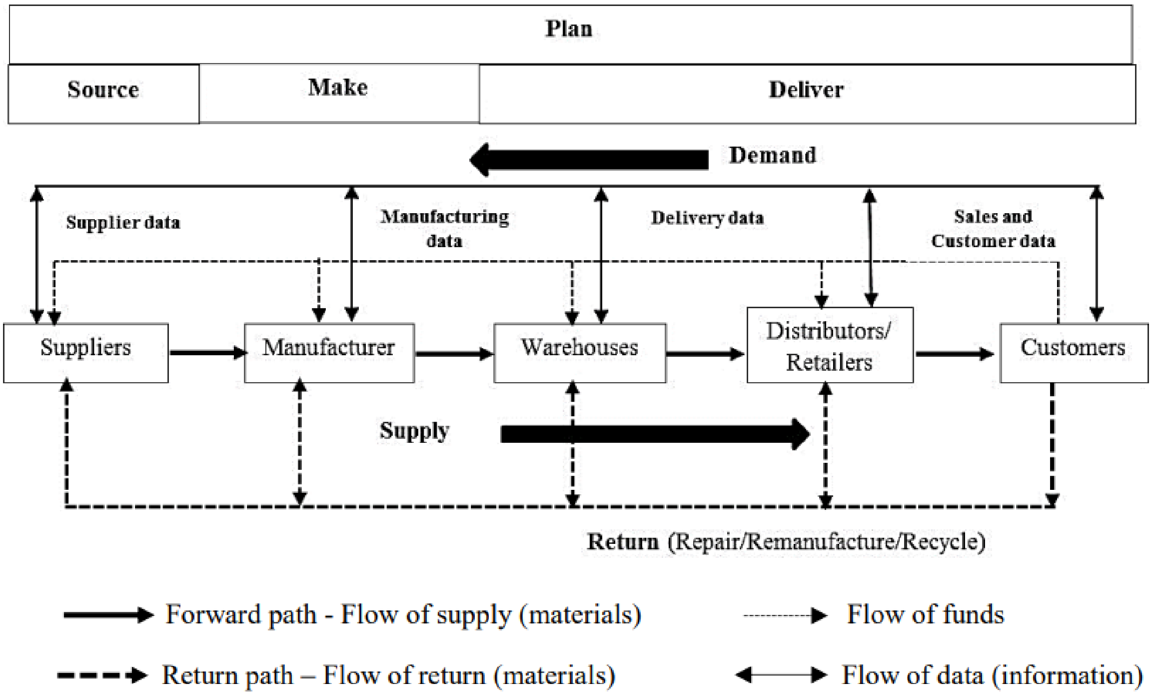

Figure 10: Data driven general supply chain structure (Biswas & Sen, 2017:7).

Supply chain insight is achieved by sharing data that is collected and generated at the nodes across the supply chain network. An aspect of supply chain performance relies on process integration and the integration of people and organisation which are enabled by information technology (IT) (Biswas and Sen, 2016). Process integration involves the coupling of at least two processes through shared systems and automated functions (Lockamy and

McCormack, 2004). By integrating supply chain processes and collecting data at each supply chain activity one has access to the necessary data to measure supply chain performance (Biswas & Sen, 2017:6).

Table 2: Types of data generated at different nodes of a supply chain (Biswas & Sen, 2017:6).

Node	Data generation
Supplier	Design data, Order status, Stock level, Schedule, Shipment & Routing, Return/Dispose, Finance data (e.g., a/c receivable, tax, pricing etc.)
Manufacturing	Basic/Activity data, Design data, forecasting data, Prod. Plan/schedule, Capacity planning data, Process data (Lot size, cycle time, takt time, throughput time, process capability etc.), Yield data, Quality/Reliability data (FTR, % rejection, % failure etc.), Stock (RM/WIP/FG), Maintenance records, Customer feedback data, Vendor data, People data, Finance data (wage, conversion cost etc.), Return/dispose
Warehouse/ Distributor/ Retailer	Demand, Stock level, Schedule, Shipment & Routing, Order, Return/Dispose, Customer feedback, Finance data (pricing, payment etc.)
Customer	Point of sales (POS), Order status/ Demand, Product feedback, Customer opinions, Payment, Delivery, New product, Promotion/Recommendation, Return/ Dispose

Organisations are now investing in advanced analytics capabilities to better understand customer intentions/behaviours and inform supply chain operational decision making, commonly referred to as SCA (Srinivasan and Swink, 2018). Souza (2014:595) describes SCA as the use of “information and analytical tools” that informs decision-making throughout the supply chain. These tools can be further classified as descriptive, predictive, and prescriptive analytics Souza (2014:595).

3.1 Descriptive Analytics

Descriptive analytics makes use of information that is flowing through the supply chain and provides insight about its current state (Souza, 2014:595-596). The use of the descriptive analytics enables the business to understand its performance and provides context for stakeholders to interpret the data (Sombi, 2021). An extension of descriptive analytics is referred to as "diagnostic analytics" and helps identify reasons for events that have occurred in the past, while also contextualising the relationships among datasets (Lepenioti, Bousdekis, Apostolou and Mentzas, 2020).

3.2 Predictive Analytics

Predictive analytics, as defined by IBM (2019), aids Organisations in performing business scenario analysis and identifies the associated business implications of the respective scenarios. Abbott (2014:5) defines this analytic technique as supervised learning, where the practitioner deduces the output models from data-driven algorithms rather than assumptions. Eckerson (2007:6) indicates that predictive analytics techniques include statistics, machine learning, neural computing, robotics, computational mathematics, and artificial intelligence. It should also be noted that in supply chains, predictive analytics tools make use of historical data in order to predict future (Chae & Olson, 2013:16). This is achieved by identifying patterns in the input supply chain information and forecast future behaviour (Chae & Olson, 2013:16).

3.3 Prescriptive Analytics

Souza (2014:596) highlights that the outcome of descriptive and predictive analytics serves as an input to prescriptive analytics. Prescriptive analytics highlights the ideal state of the supply chain and its associated processes (Souza, 2014:596). Prescriptive analytics focuses on the ways in which the organisation while taking also taking consideration their current supply chain constraints (Biswas & Sen, 2007:9). The prescriptive analytics process involves the process of forecasting of product sales as a point of initiation for defining anticipated revenues (Fan, Che, and Chen, 2017: 90). In addition to this, decisions about production, operations and marketing strategies can be shaped by the outputs of the forecasted product sales (Fan *et al*., 2017: 90). Other literature associate prescriptive analytics capabilities aspect with Sales and Operations (S&OP). Goh and Eldridge (2019: 80-94) define S&OP as an array of business processes and technologies that allow an organisation to respond to the variability of supply and demand. The authors also cite that S&OP enable organisations to determine their optimal resource allocation while also determining their most optimal supply chain mix (Goh & Eldridge, 2019: 80-94).

3.4 Supply Chain Analytics for Supply Chain *Planning*

Souza (2014: 595-605) links the application of *Plan* processes to demand forecasting on both a strategic and tactical level. The author argues that data mining techniques as well as traditional forecasting techniques can be applied in the planning process. This sentiment is shared by Rey, Kordon, and Wells (2012:6), where the authors are of the view that the combination of data mining techniques and forecasting models have the potential to yield results that then able organisations to make informed business decisions. Zhu, Song, Hazen, Lee, and Cegielski (2018: 50) refer to the analytics capability in the *Plan* function as "Analytics Capability in *Plan* (ACP)". The authors argue that this capability involves the use of data analysis to enable demand planning Zhu *et al*. (2018:51).

3.5 Analytics Capability in *Source*

The ordering and scheduling of goods and services is described by the *Source* processes (APICS, 2019). The application of SCA in the *Source* function of the supply chain improves the consolidation of inbound supply chain (Stefanovic and Stefanovic, 2009: 217-245). In addition to this, Wang, Gunasekaran, Ngai, and Papadopoulos (2016:4) identify the application of SCA in the *Source* function as a tool to enhance supplier relationship management. By analysing organisational spend data and extrapolating insight from this data, the *Source* function is enabled to strategically source commodities or services on a cost-effective basis (Wang, Gunasekaran, Ngai and Papadopoulos, 2016). Zhu, Song, Hazen, Lee, and Cegielski (2018: 50) perceive this application of SCA as a tool to manage supply chain risks that are associated with suppliers of *Source* markets, as well as, managing their supplier performance. Analytics capabilities in the supply chain *Source* function can also be linked to procurement analysis. Procurement analytics is concerned with the collection and analysis of procurement data and includes activities such as generating procurement spend analysis reports and predicting budget future decisions using analytics (Sievo, 2022).

3.6 Analytics Capability in *Make*

The SCOR model describes the creation of content for services and the transformation of raw material to finished goods as processes associated by the Make aspect of SCOR (APICS, 2019). The *Make* function of the supply chain describes the creation of content for services and the transformation of raw material to finished goods as processes. Themes related to the *Make* process in early SCA literature include inventory optimization through the application of algorithms. Perumalsamy and Natarajan (2010: 1-8) in their paper, highlight the relationship between customer service levels and the effective management of supply chains. The authors argue that by optimising inventory levels through the application of algorithms, a firm can minimise holding costs while keeping enough inventory to satisfy customer demand. In their methodology, the authors made use of MATLAB, which is a programming software that can be used to predict the objective function of an algorithm while also considering the input historical data.

3.7 Analytics Capability in *Deliver*

The fulfilment and maintenance of customer orders is described by activities that are associated with the *Deliver* process (APICS, 2019), which includes activities such as warehousing, order management and the associated logistics of the delivery process. SCA can facilitate the order fulfilment process. Trkman, McCormack, De Oliveira, and Ladeira (2010) associate this process with the application of Business Analytics tools to deliver products to the market in an efficient manner. This is evident in organisations where route data and software are integrated and leveraged to optimise the route allocation of vehicles (Winkenbach:2018).

3.8 Analytics in ***Return***

The *Return* process aspect of the SCOR model encompass the management of reverse logistics and disposal of nonconforming products (Mollenkopf, Russo, and Frankel, 2007:569). Rogers, Melamed and Lembke (2012: 109) differentiate between analytical and simulation models that can be used to manage and optimise *Return* function processes. The authors define analytical models in the *Return* function as “models that employ analytical abstraction consisting of equations and constraints these models can either be static or dynamic”. Simulation models on the other hand, make use of historical data to replicate the system components while also incorporating the associated business rules to describe and evaluate the system under consideration (Rogers et. Al. ,2012: 110).

The growth of customer expectations in DSC networks has fuelled the need for organisations to not only understand their customers, but also anticipate their needs. This digital transformation of supply chains has also led to increased customer expectations, which is driven by online trends and a drift, by organisations towards an individualised and customised customer offering (Alicke, Rexhausen, and Seyfert, 2017). As a result, we find ourselves operating in “customer driven supply chains” or “demand driven supply chains” as referred to by Chi, Huang and George (2020). Thus, the motivation for organisations to invest in Customer Relationship Management (CRM) technology. CRM is an approach that guides the integration of resources and information across the supply chain in such a way that customer needs are well understood and met by the organization. Goldenberg (2002:9) defines this as the integration of people, processes and technology.

3.9 Customer Relationship Management in Supply Chains

The increased importance of the customer has subsequently resulted in organisations to moving from a SCM to a Demand Chain Management (DCM) view. The demand processes that make up this ‘chain of demand’ are associated with the understanding, creation and stimulation of customer demand (Bumblauskas, Bumblauskas, Sapkota, Misra and Ahsan, 2017). This customer demand is captured by linking the organisation's back-office operations to the customer "touch points". The back-office links consists of functions such as finance, operations, and human resources, to name a few. Customer "touch points" include supply chain related activities such as retail distribution (Chen and Popovich, 2003), and these "touch points" are integrated through CRM technology solutions and data warehouses as illustrated in Figure 11. Although CRM is an area of market research that has developed over the years, the importance of the end-consumer is still being neglected by operations and SCM researchers, leaving this aspect usually as an after-thought (Bumblauskas *et al*., 2017).

CRM innovation technology creates a platform to for the organisation to identify and analyse common and unique customer behaviour patterns (Chen and Popovich, 2003). Among the notable CRM technologies is on-line analytical processing (OLAP) servers, that facilitate the collection and analysis of business data which is then used for data-driven decision making. OLAP servers enable the process of extracting insight from data and are typically supported by data warehousing. Data warehousing as a collection of decision support technologies that enable practitioners to make informed business decisions. These technologies typically collect data from various operational databases. Information is extracted by means of OLAP queries and this information is subsequently analysed to answer business questions (Queiroz-Sousa and Salgado, 2019; and Biswas, 2020). By identifying the data that is available and useful to measuring performance, one can implement the necessary technologies and controls that will facilitate information flow and their interpretation, which then enables the organisation to make better and faster decisions to meet their customer requirements (Govindan, Cheng, Mishra,and Shukla, 2018).

Existing literature links demand analysis to advanced analytics capabilities in supply chains through application specific research, for example, focusing on data-driven approaches to demand forecasting (Pereira and Frazzon, 2021), and cloud-based BDA for customer insight-driven design innovation (Liu *et al*., 2020). An advanced Google Scholar search for literature containing both "Customer Relationship Management" and "Supply Chain

Analytics” as key words did not yield results. However, a similar search using “Customer Relationship Management” and “Big Data Analytics” yields only 9 results, see Table 3.

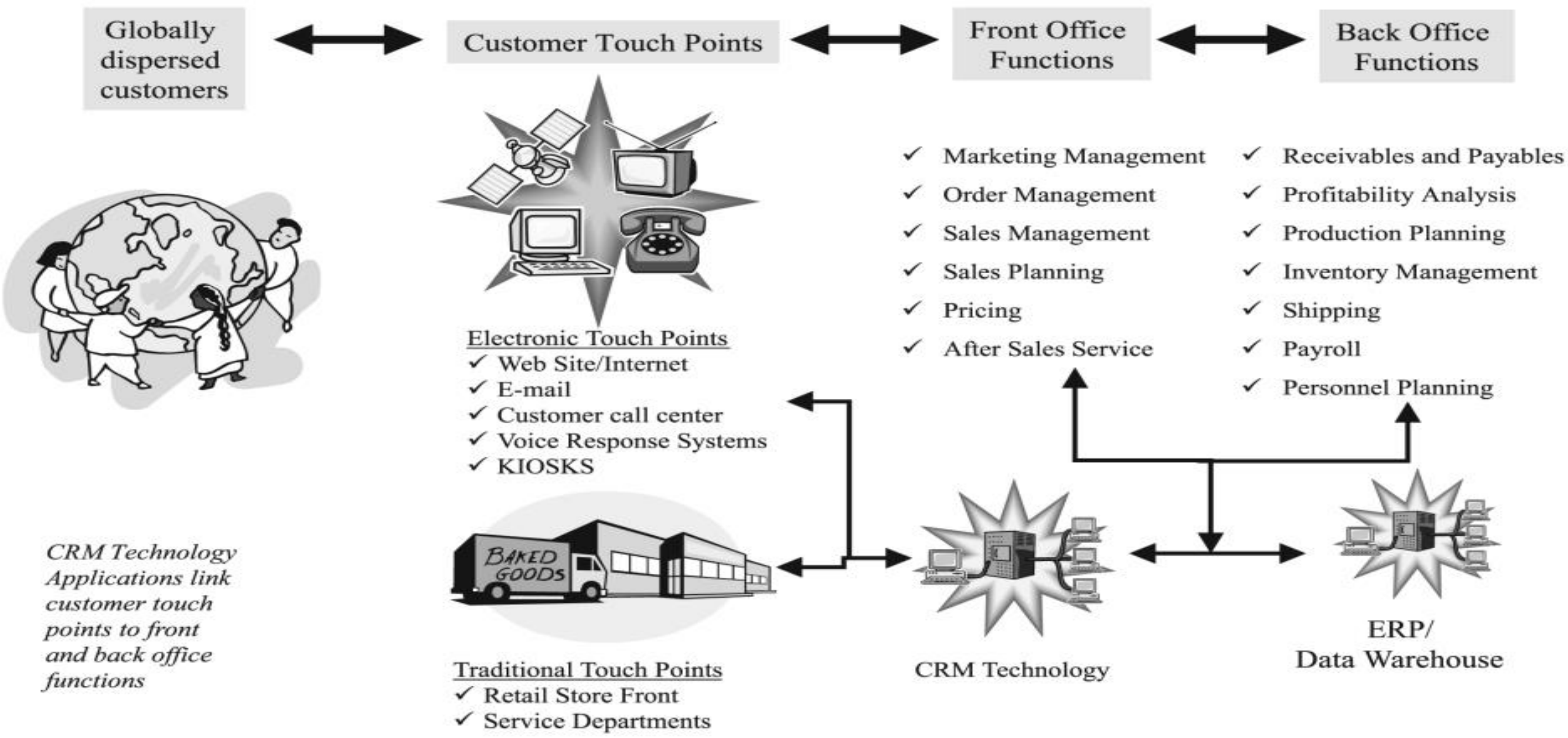

Figure 11: CRM technology linking the front and back-office functions (Chen and Popovich, 2003).

Table 3: Results from advanced Google Scholar search for literature titles that have both "Customer Relationship Management" and "Big Data Analytics" as key words as 1 July 2022.

Title	Aim of study	Citation
A review of big data analytics for customer relationship management	This research paper attempts to analyse research of Big Data Analytics, Data Mining techniques, Big Data Analytical Frameworks that can be used in Customer Relationship Management	Perera, W.K.R., Dilini, K.A. and Kulawansa, T., 2018, "A Review of Big Data Analytics for Customer Relationship Management," *2018 3rd International Conference on Information Technology Research (ICITR)*, 2018, pp. 1-6, doi: 10.1109/ICITR.2018.8736131
Big Data Analytics for Customer Relationship Management: A Systematic Review and Research Agenda	The paper aims to study the extant state of big data analytics for customer relationship management through the method of systematic literature review.	Sharma, S., 2020, April, Big Data Analytics for Customer Relationship Management: A Systematic Review and Research Agenda. In *International Conference on Advances in Computing and Data Sciences* (pp. 430-438). Springer, Singapore.
Investigating the impact of big data analytics on perceived sales performance: The mediating role of customer relationship management capabilities	This study proposed a research model to investigate the impact of BDA on perceived sales performance in accordance with the resource-based view (RBV) and dynamic capability theory	Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., Abbas, A. and Zahid, R., 2020. Investigating the impact of big data analytics on perceived sales performance: The mediating role of customer relationship management capabilities. *Complexity*, 2020 .
Impact of big data analytics on sales	This study investigates the impact of big data analytics	Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., Luqman, A.

performance in pharmaceutical organizations: The role of customer relationship management capabilities	(BDA) on CRM capabilities and the sales performance of pharmaceutical organizations	and Zahid, R., 2021. Impact of big data analytics on sales performance in pharmaceutical organizations: The role of customer relationship management capabilities. *Plos one*, 16(4), p.e0250229.
Organizational Success Factors in the Implementation of Big Data Analytics for Customer Relationship Management	The contribution of this research is in the development of a formal success model for BDA implementation in the CRM domain	Duang-Ek-Anong, S., 2019. Organizational Success Factors in the Implementation of Big Data Analytics for Customer Relationship Management. International Journal of Simulation--Systems, *Science & Technology*, 20(5).
Review of the Plan for Integrating Big Data Analytics Program for the Electronic Marketing System and Customer Relationship Management: A Case Study XYZ Institution	The study explores how a Big Data Analytics Program can be integrated for The Electronic Marketing System and Customer Relationship Management	Sudianto, I., 2019. Review of the Plan for Integrating Big Data Analytics Program for the Electronic Marketing System and Customer Relationship Management: A Case Study XYZ Institution. *arXiv preprint arXiv*:1908.02430.
Integrating customer relationship management with big data analytics in retail stores: a case of hyper-star and metro	Study investigates the benefits of integrating CRM and Big Data using in retail stores of Pakistan as a case study.	Mahesar, H.A., Chaudhry, N.I. and Tariq, U., 2017. Integrating customer relationship management with big data analytics in retail stores: a case of hyper-star and metro. *Journal of*

		Business Strategies, 11(2), pp.141-158.
Big data analytics toward intelligent mobile service provisions of customer relationship management in e-commerce	This paper will introduce multi-agent systems and their applications from a data mining from a Customer Relationship Management (CRM) aspect	Xu, L. and Chu, H.C., 2016. Big data analytics toward intelligent mobile service provisions of customer relationship management in e-commerce. *Journal of Computers*, 26(4).
Use of Big Data Analytics for Customer Relationship Management: Point of Parity or Source of Competitive Advantage?	Objective was to determine to what extent organizational big data customer analytics use (CA use) improves customer-centric and financial outcomes, and to assess how antecedent factors influence CA use.	Suoniemi, S., Lars, M.W., Munzel, A., Zablah, A.R. and Straub, D.W., 2014. Use of Big Data Analytics for Customer Relationship Management: Point of Parity or Source of Competitive Advantage?

There is a low uptake of the advanced analytics approach by organisations due to the lack of understanding of how it can be implemented, as well as the incapability to identify appropriate data to be harvested (Nguyen *et al*., 2018). This challenge is further aggravated by the limited research that integrates the digital and physical worlds within supply chains (Pereira and Frazzon, 2021).

3.10 The Proposed Integration of Customer Relationship Management and Supply Chain Analytics Capabilities

Parallel to application of SCA, customer-demand is integrated into the DSC operations by analysing data and making managerial decisions based on the insight. CRM strategies are supported by big data and as a result, organisations are required to establish supporting accurate data analytics (Anshari *et al*., 2019. As discussed in Section 3.9, CRM is an approach that is widely recognised to gather, examine, understand, and translate information that is related to customers to guide managerial actions (Rajput *et al*., 2018). An understanding of customer needs thus allows organisations to coordinate their supply chain activities in a way that the customer needs are met as much as possible and this is achieved by sharing customer information both internally and externally throughout the supply chain (Fredendall and Hill, 2000). Hence, CRM is not intended to be viewed as an information technology (IT) initiative, but rather, as a business strategy that seeks to derive business value which is enabled by IT (Yerpude and Singhal, 2017).

Based on both CRM and SCA literature that has been discussed in this thesis, set of hypotheses is proposed and will be tested by means of a set of simultaneous equations within the Structural Equations Model (SEM) framework. A set of hypotheses is proposed to answer the over-arching research that is presented in this chapter, that is:

> *What are the capabilities that are required to integrate customer demand to the digital supply chain network?*

3.10.1 People Capabilities

$H_{1,1}$: *A customer-centric organisational culture has the potential to improve the organisation's SCA capabilities.*

A customer central platform model forms the foundation of a DSC (Agrawal and Narain, 2018), and an organisational culture is a strong determining factor of an employee's willingness to adopt to changes - the resistance thereof results in a divided organisation (Büyüközkan and Göçer, 2018). Members of the DSC therefore require organisational realignment, where they evolve from making reactive, to making predictive and prescriptive supply chain decisions (Sabri, 2019).

$H_{1,2}$: *The effective implementation of a Customer-Relationship-Management strategy is dependent on top-management buy-in.*

CRM enables the collaboration between staff members as well as organisation readiness. Strategic CRM aims to focus and improve knowledge about customers which is then used to gain insight and enhance the customer interaction (Juneja, 2021). Organisational readiness includes changes within organisational culture and buy-in from top management in the organisation (Chen and Popovich, 2003). It is critical for the highest level of management to drive the notion of a DSC and its associated approaches (Büyüközkan and Göçer, 2018), that is, the establishment of a CRM strategy to drive SCA capabilities in this case.

3.10.2 Process Capabilities

$H_{2,1}$: *It necessary to establish customer-centric supply chain processes in order to improve SCA capabilities.*

The process component of CRM makes use of a business process re-engineering approach to meet customer needs, in which the organisation processes are to be re-designed in such a way that focus is shifted from a product-centric agenda to a customer-centric agenda (Rahimi, 2017). The reconfiguration of supply chain processes to meet customer needs supports the achievement of a customer-centric / demand-driven supply chain (Martinelli and Tunisini, 2019). These customer-centric supply chain processes involve the integration of market signals and customer information in supply chain processes and enable predictive analytics (Oti-Yeboah, 2021). The digitalised supply chain is therefore to establish end-to-end supply chain processes that connects its customers and suppliers by eliminating non-value adding activities and touchpoints of functions and processes (Sabri, 2019).

$H_{2,2}$: *The integration of information flow between the supply chain processes (planning, sourcing, making/raw material transformation, delivery, return and enabling processes) improves SCA capabilities*

By integrating supply chain processes, and by collecting data at each supply chain activity stage, the flow of information between supply chain activities is facilitated and one then has access to the necessary data to measure supply chain performance (Biswas and Sen, 2017). In the manufacturing and retail industry, for example, data is collected using technologies such as point of sales (POS), Global Positioning Systems (GPS) and radio frequency identification (RFID) and is used for analysis and decision-making (Arya *et al*., 2017).

3.10.3 Technology Capabilities

$H_{3,1}$: *Organisation's investment in Business-Intelligence tools (such as Power BI, QlikView, SAP associated platforms, etc.), improves SCA capabilities within a function/business unit*.

The technology aspect of CRM focuses on the use of business intelligence tools that collect and interpret such customer data, and in the context of supply chains, data is linked to the customer information, sales information, and logistics information to name a few (Biswas & Sen ,2017). Sahay and Ranjan (2008) define business intelligence as technological platforms, such as on-line analytical processing (OLAP) servers, that facilitate the collection and analysis of business data which is then used for data-driven decision making. Chae and Olson (2013) also highlight that business intelligence and business analytics can be viewed to similar, in that both leverage the analytics of data and provide reports about the analysed information.

$H_{3,2}$: *Training of staff on Business-Intelligence tools (such as Power BI, QlikView, SAP associated platforms, etc.), improves SCA capabilities in a function/business unit.*

The use of technology in DSC is supported by supply chain talent and knowledge. Knowledge related to technology management, as well as technical, relational and business knowledge is a key supply chain analytics capability (SCAC) (Wamba and Akter, 2019). The training of employees to effectively use technology tools translates to the improvement, streamlining and optimisation of supply chain processes and this ultimately translates to a reduced cost to serve customers (Bemelmans, 2017).

$H_{3,3}$: *The nature of the petrochemicals industry hinders an organisation's ability to effectively implement SCA capabilities.*

Time, cost, and effort have been cited among the challenges in establishing an SCA enabled environment. These challenges are associated with the high acquisition and maintenance cost software, long horizon for benefit realisation and lack of knowledge around adopting SCA systems (Brahme, 2021). The oil and gas industry, in particular, falls short when it comes to investing and leveraging digital technology in comparison to other industries. As a result, there is an inability to share information across the supply chain and facilitate integrated planning for effectively and efficiently meeting customer requirements (Stratton, 2018).

3.11 Model Development

Two Structured Equation Models (SEM) for the integration of CRM and SCA capabilities are proposed. A high-level description of SEM can be found in sub-section 3.12.1. Three latent variables are explored in this study, namely, People, Process and Technology capabilities. These variables were derived from a review of literature and were identified as drivers of CRM. A high-level description of SEM can be found in sub-section 3.12.1.

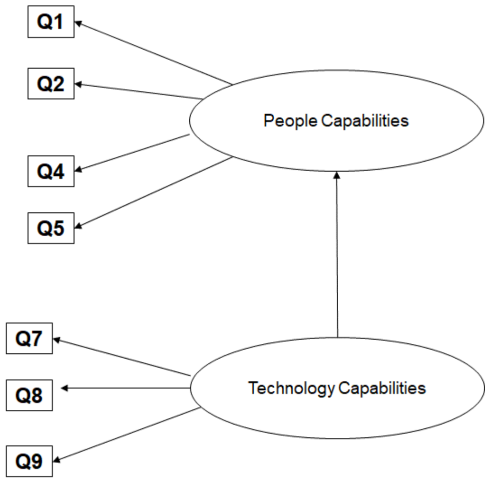

Figure 12: Proposed Model.

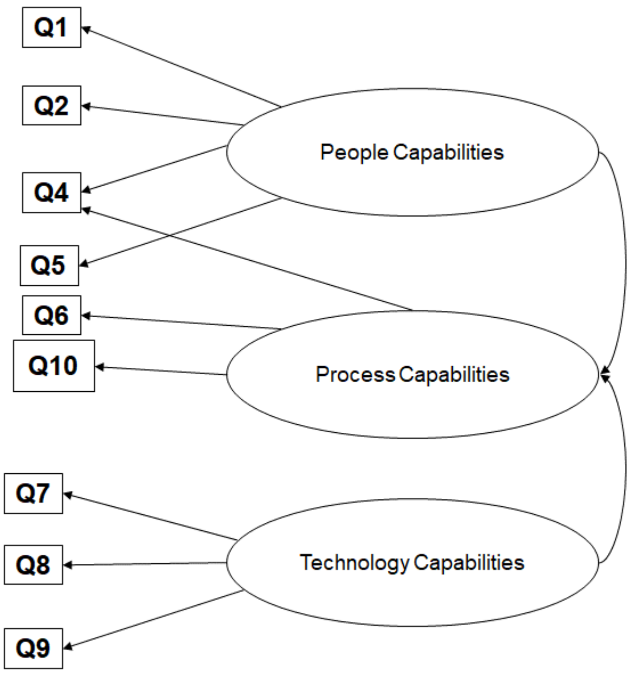

Figure 13: Proposed Model-2.

The ecosystem of the scope of the study comprises of variables that have both direct and indirect relationships and the following models are proposed to achieve the research objective: Model-1 evaluates the relationship between People and Technology capabilities and Model-2 investigates how the relationship between People and Technology capabilities enable Process capabilities. The following set of questionnaire items were included in the survey:

Questions 1-3:

1. How many years have you worked in the petrochemicals industry?
2. How many years of experience do you have in your field?
3. In which area of expertise would you categorise your current role within the organisation?

For questions 4-10, the following definition for SCA was provided within the questionnaire: “An approach that integrates people, processes and technology across the organization by applying techniques that makes use of data and business intelligence platforms.” - Biswas and Sen (2015).

4. Based on your experience in your function, would you agree that a customer-centric culture has the potential to improve your organisation's SCA capabilities?
5. In your function/business unit, would you say that the effective implementation of a Customer-Relationship-Management strategy is dependent on top-management buy-in?
6. In your function/business unit, would you say that it necessary to establish customer-centric supply chain processes in order to improve SCA capabilities?
7. In your function/ business unit, has the integration of information flow between the supply chain processes (planning, sourcing, making/raw material transformation, delivery, return and enabling processes) improved SCA capabilities?
8. Has your organisation's investment in Business-Intelligence tools (such as Power BI, QlikView, SAP associated platforms, etc.), improved SCA capabilities within your function/business unit?
9. Has the training of staff on Business-Intelligence tools (such as Power BI, QlikView, SAP associated platforms, etc.), improved SCA capabilities in your function/business unit?
10. Based on your experience, does the nature of the petrochemicals industry hinder your organisation's ability to effectively implement SCA capabilities?

3.12 Methodology and Data Collection

A case study approach is adopted in this investigation as such an approach focuses on establishing a sense of understanding within a specific single setting (Eisenhardt, 1989:534). Yin (1981-101) highlights that such case studies are commonly used to test theory, and additionally, as deduced by (Stouffer, 1941:349-357), single-case designs have the capability of providing valid results at the same level of significance as critical experiments do. The methodology supports the deconstruction and construction of a phenomenon of interest which is then viewed through various theoretical lenses thus enabling multiple aspects of the phenomenon to be revealed and understood within that particular context (Baxter and Jack 2008).

A web-based survey was designed and administered via email to potential participants within the participating organisation (See Appendix A). The survey questions were linked to the research variables to be tested, and contained 10 multiple-choice close-ended questions, which would be useful to validate the study hypotheses (Aithal and Aithal, 2020:3-4). The participating organisation was a petrochemicals company that comprises of approximately 30 000 employees, working across about 30 countries. The organization is referred to herein as “Petrochemicals Company (PC)”. This PC has been part of the South African petrochemicals industry for over 70 years, and has undergone, through significant phases of transformation, changes that have occurred within its supply chain. As a result, the PC has significantly invested in technology platforms, such as SAP (a German multinational software company), with the goal of harvesting data that can be used to make informed business decisions.

The survey was designed on Qualtrics ®, a cloud-based platform that is used to create and distribute web-based surveys. Permission and ethical clearances were obtained before commencement of the survey. Prior to the administering of the questionnaire, a pilot of the survey was sent to two supply chain experts, based on their experience in the field, via electronic mail (e-mail), and a mock-survey was also conducted among the authors to confirm the operational process. Feedback was reviewed, and the questionnaire was improved accordingly before the final version of the survey was sent out. Email invitations, with a link to the web-based survey, were sent to 62 individuals at the PC based on the sampling frame specification that required that the targeted individuals were those known to be assigned to the supply chain functions within the PC, such as technology enablement and inventory management within the PC. The participants were also informed that their responses would remain anonymous. A window of five-days was initially provided to complete the survey, and a follow-up email was sent thereafter. The combined timeline of the pilot survey and the final survey was five weeks between April-May 2021. The data was downloaded from Quantrics® as a .csv file, and analysed in R, an opensource language and computing environment, within the RStudio environment (Version 1.4.1717). Specifically, the following packages, among others, have been used: *ltm* (Rizopoulos, 2022), *lavaan* (Rosseel, 2022), *semPlot* (Epskamp , 2022), *tidySEM* (Van Lissa, 2019).

Ethical clearance was obtained from both the participating PC and the University of Pretoria. Participation in the survey was anonymous and voluntary (see Appendix C). All collected data (i.e., original dataset with perhaps identifiable information) and other related information accumulated for this research study / research project was stored in a secure storage space (i.e., electronic data or hard-copy data). This includes data collected and stored via electronic platforms (e.g., Qualtrics, Survey Monkey) and the downloaded versions of these original datasets. Access to the original data was limited to the researcher and study supervisor. All data stored on the mentioned platforms will be disposed of and destroyed after the prescribed period and by means of the prescribed method as defined by the University of Pretoria Information Management policy.

3.12.1 Structural Equation Model

A Structural Equation Model (SEM) framework was used to evaluate empirically the hypothesized relationships between the discussed CRM capabilities and the SCA capabilities based on the survey data. SEM is a theoretically driven data analytics approach which evaluates priori specified hypotheses as per identified causal relations between measured and /or latent variables (Mueller and Hancock, 2018). Measurement error in the observed variables is accounted for in SEM, as a result, a more precise measurement of the theoretical concepts of interest is obtained (Hair, *et.al*).

Path models are diagrams that are used to depict the hypotheses and relationship among variables in a SEM (Bollen 2002). Latent variables are elements in the SEM that capture the conceptual variables as defined by the researcher in their theoretical model(s). These latent variables, also referred to as constructs, are visualised as circles or ovals in the path model (Sarstedt, Ringle, and Hair, 2021).

Model-1 and Model-2, as described above, were tested via CFA to test the strength of the relationships between the observed and latent variables. SEM are commonly utilized as a statistics technique that assesses the factor structure of a set of observed variables and it enables scholars to test for construct validity (Shamout, 2019). In this thesis SEM was used to analyse and test the proposed models. R software was used to evaluate the models, which is a free, opensource, and cooperatively developed software (Fox, 2019).

Data

The survey consisted of 10 closed-questions, each with a set of options. Although the survey was sent out to 62 individuals, only 28 responses were received. The sample criteria were individuals that perform activities that directly impact customer order fulfilment for both petrol and diesel. Follow-up emails were sent out to all 62 individuals. A summary of the responses, and non-response (empty), by questions, from the 28 respondents is presented below. Note the column "Response" reflects the option chosen by the respondent for the question, with questions 1, 2, 4, 6 and 8 giving respondents three possible answers to choose from; and question 3 giving respondents eight options to choose from.

Specifically, questions 1 and 2 related to work experience, such as years of experience working in the current petrochemical industry (Q1); and years of experience in the field in general (Q2), which is and summarised below:

Table 4: Count of survey response by questions.

Response	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
1	18	2	6	25	17	19	14	9	6	2
2	7	7	3	1	9	8	10	10	10	3
3	3	19	3	2	1	1	3	9	10	8
4			3				1		2	3
5			9		1					12
6			3							
7										
8			1							

Table 5: Cross-tabulation of Q1 (row) and Q2 (column).

	10+years	5-10years	<5years	Total
<5years	1	1	16	18
5-10years	1	5	1	7
10+years	0	1	2	3
Total	2	7	19	28

Question Q3 asked the area of expertise of the respondent and was not intended to be used in any of the SEM models in the paper. Below we summarise the response to Q3 which had seven pre-specified options, and option '8' being for 'Other', with no one choosing option '7: Customer service'.

The next seven questions related to the study, intending to capture the three latent notions of People capability, Process capability and Technology capability, and response options were in the form of Likert-response. People capability was intended to be captured by questions 1, 2, 4 and 5; Process capability was intended to be captured by questions 4, 6 and 10; while Technology capability was intended to be captured by questions 7, 8 and 9.

3.13 Results

The analysis herein initially interrogates the data generated correlation between the measurement variables, namely Q4-Q10. Thereafter, confirmatory factor analysis within the SEM framework is performed corresponding to the two models namely, Model-1 and Model2, comprising of both the measurement variables and the latent variables.

3.14.1 Correlation Results

From the correlation matrix for Q4-Q10 in Table 6, we deduce that to enable SCA capabilities, a customer-centric organisational culture (Q4) is significantly positively correlated with the integration of information flow between the supply chain processes (Q7), the training of staff on Business-Intelligence tools (Q9) and the establishment of customer-centric supply chain processes (Q6) at 0.55, 0.42 and 0.39 respectively.

Table 6: Correlation between questions 4-10.

	Q4	Q5	Q6	Q7	Q8	Q9	Q10
Q4							
Q5	0.10						
Q6	0.39*	0.20					
Q7	0.55**	0.04	0.02				
Q8	0.25	-0.05	0.00	0.55**			
Q9	0.42*	-0.11	0.08	0.53**	0.51**		
Q10	-0.08	0.33	-0.06	0.05	0.14	0.04	

Interestingly, Q4 was identified as a People Capability in the proposed SEM models, and it was found not to be significantly correlated to the top-management buy-in to Customer-Relationship-Management strategy (Q5), which is also classified as a People Capability in the model. Secondly, from Table 6, it is observed that top-management buy-in to Customer-Relationship-Management strategy (Q5) was found not to be significantly correlated to any of the other defined variables. Third, the establishment of customer-centric supply chain processes to enable SCA capabilities (Q6), other than with Q4, is not significantly correlated with other questions. This observation supports the theoretical view that the digitalised supply chain needs to establish end-to-end supply chain processes that connects its customers and suppliers, as discussed in Section 3.9.

Further from Table 5 the following is observed: (i) the integration of information flow between the supply chain processes (Q7) is significantly correlated with the organisation's investment in Business-Intelligence tools to improve SCA capabilities within your function/business unit (Q8) and the training of staff on Business-Intelligence tools (Q9) at 0.55 and 0.53 respectively, along with Q4 (as previously observed); (ii) The organisation's investment in Business-Intelligence tools (Q8) is significantly correlated to the training of staff on Business-Intelligence tools (Q9), at 0.51 (a significant correlation is also observed Q8 and Q4 as previously discussed); (iii) Other than with Q4 and Q7, the training of staff on Business-Intelligence tools (Q9) was found not to be positively correlated with any other question. (iv)

Lastly, the question relating to the nature of the petrochemicals industry hindering the organisation's ability to effectively implement SCA capabilities (Q10) was found not to be significantly correlated with any of the questions. A negative, yet insignificant, correlation was however observed between Q10 and Q4 at -0.08. Similarly, the correlation between Q6 and Q10 was found to be -0.06. This suggests that challenges to creating a SCA enabled environment are not associated with the end-to end supply chain processes and inherent business risks of a specific value chain.

3.14.2 Structural Equation Analysis Results

Cronbach's alpha is used to measure the internal consistency of questions in surveys. The measure provides an estimation of the reliability of responses to a questionnaire and indicates stability of the questionnaire (Bujang, Omar, and Baharum, 2018). The Likert scale response options, for the two models in this thesis are as follows: for Model-1 Cronbach's alpha = 0.386, which is low, given the small sample size (28), and recalling that it consisted of only 7 Likert scale questions (Q4-Q10); and for Model-2, Cronbach Alpha = 0.393, which is marginal improvement.

The CFA results from the SEM analysis corresponding to Model-1 and Model-2 are presented below graphically, with the p-value for Model-1 and Model-2 being 0.034 and 0.457 respectively. Note, the small number of measurement variables, while on the one hand was good with regards to the notion of survey fatigue, on the other hand it also resulted in some of the evaluated variances being negative, which can be the result of several issues such as the small sample size being small (28), the models being mis-specified, or the presence of outlier responses.

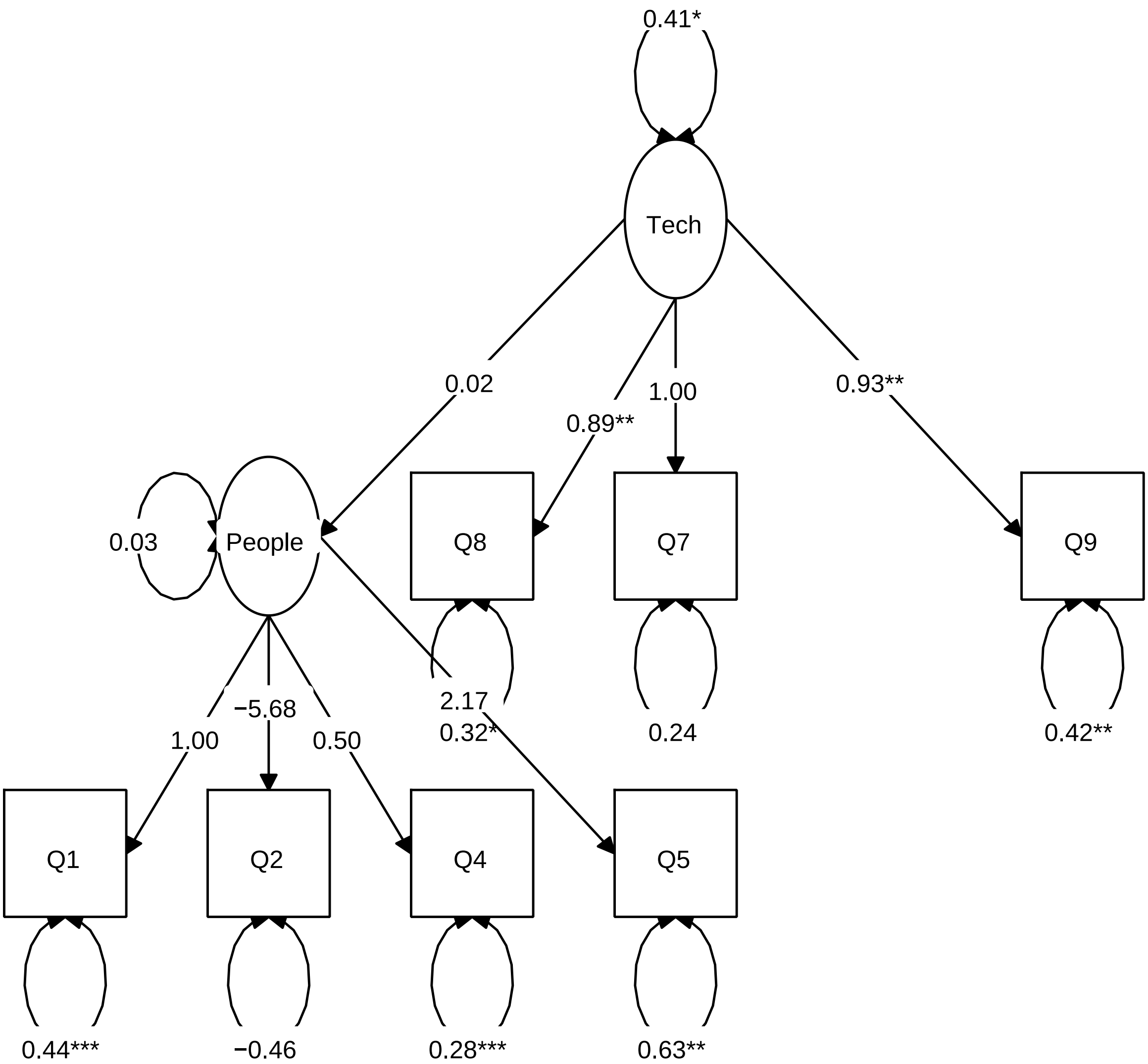

Figure 14: Structural Equation Model (SEM) results of proposed Model-1 for the integration of CRM and SCA capabilities.

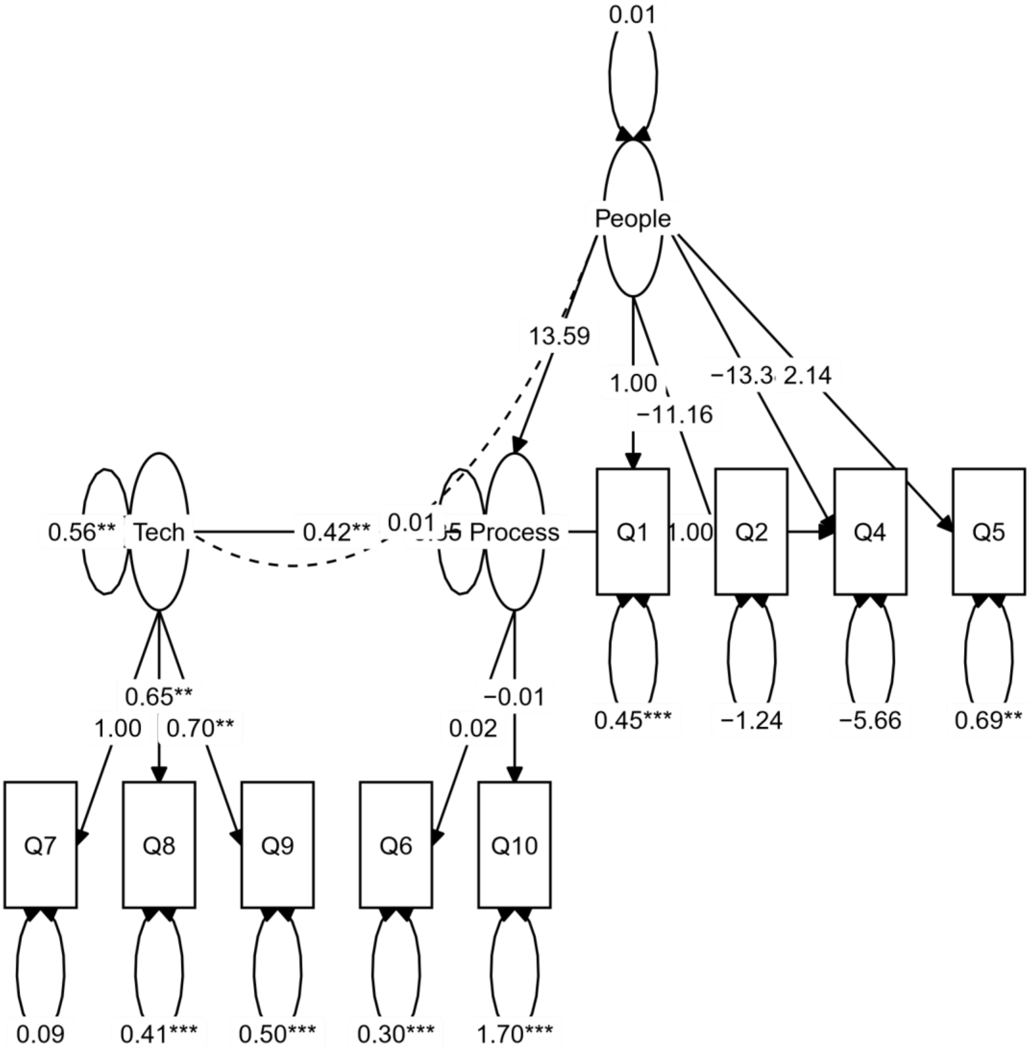

Figure 15: SEM) results of proposed Model-2 for the integration of CRM and SCA capabilities.

3.14 Discussion of Findings, and Concluding Remarks

This research was a novel exercise in obtaining primary responses through a single-case design approach to test the proposed theory via two models integrating CRM and SCA capabilities in relation to three latent variables namely, People, Process and Technology. The target respondents were those known to be assigned to the supply chain functions within the participating company. Even though the survey was only 10-questions long, within the planned survey window, only 28 of the 62 potential participants responded. While this was not ideal, the data was analysed using various descriptive summarisation methods, correlation as well as CFA outputs corresponding to the two proposed model, one including only the People and Technology latent variables (Model-1), and the other an extension of Model-1 that also included the Process latent variable (Model-2).

From the correlation analysis of Q4-Q10 it was observed that personnel within this case study environment associate Technology (specifically BI tools) with SCA capabilities, and that they also perceive management buy-in as a determining factor to the successful embedding of a customer-centric organisational culture. This may be attributed to the emphasis on the benefits of supply chain technology applications by organisations and reflective of the investment in technologies that most companies incorporate into their supply chain processes. These benefits include the capability of being able to collect and analyse customer information, sales information, and logistics information to name a few (Biswas & Sen, 2017). Achieving a SCA enabled environment is therefore not only dependent on the integration of information systems across the supply chain, but also on establishing an information sharing and collaborative environment among resources within and between end-to-end supply chain processes. The resistance to a customer-centric culture therefore inhibits the ability for supply chain information to flow through the organisation and this ultimately translates into a supply chain that cannot collect and analyse its customer data.

The CFA investigation incorporating the three latent variables of People, Technology and Process shed some insights. From the demographic questions, it appears that majority of the respondents were new in their role, and this may have influenced their confidence with regards to responses. From Model-1 CFA output it was observed that the Technology latent variable has significant loading on its measurement variables, while none of the loading from the People latent variable are significant. From Model-2 CFA output the observation suggests that with the introduction of the Process latent variable, the loading of Technology on its measurement variables, and on Process is significant (0.42). However, the loading of People on its measurement variables as well on Process latent variable remains insignificant. A CRM-SCA model excluding People capabilities is not an option.

This exercise has highlighted the various operational aspects for a successful CRM and SCA integration, including the heterogeneity with regards the experience of the relevant staff. It appears that relatively objective capabilities of Technology and Process are less ambiguously understood, while the subjective aspect of People capability was not as synchronously reflected in the responses in our survey. A review of these observations suggests that a follow-up survey specifically investigating the People capability may shed more light on areas for investment within similar data-driven digital supply networks.

Results of the survey also highlight that a customer-centric supply chain design is therefore critical in not only enabling SCA capabilities but also in the establishment of a customer-centric organisational culture. Furthermore, a customer central platform model forms the foundation of a DSC, therefore enabling staff to operate in this environment, increasing willingness to adopt to changes in the organisation.

Overall, the survey results affirm that there is a lack of understanding of the capabilities that are required to integrate customer demand to the DSC network, particularly People capabilities. It is therefore suggested in this thesis that to evolve from SCM organisation to a Demand Chain Management (DCM) organisation, companies need to establish a customer-centric culture, and processes. Leadership led CRM strategies are key to introducing and evaluating the missing link between the contemporary supply chain and its customers.

Keeping to the context of the South African petroleum market, and with the overarching research question being: *What are the capabilities that are necessary to perform effective supply chain analytics using customer data?*, in Chapter 4 an exploratory investigation of the predictive significance of certain relevant customer and business sentiment indices is undertaken, in conjunction with other domestic and international economic indicators, to predict South Africa’s petrol and diesel consumptions.

4 PREDICTING SOUTH AFRICA'S PETROLEUM CONSUMPTION

South Africa is an oil importing country with a limited amount of proven oil reserves of its own. Approximately 60% of SA's oil supply is sourced from the Middle East and other African countries. The remaining 40% is produced from synthetic processes by a domestic petrochemicals company using coal. There are four operational oil refineries in the country, each with a throughput of at least 100 000 barrels per day (SAPIA. 2020). Imported crude oil makes its way from the refineries and various by-products are either sold to the consumer, or undergo further processing, at various chemical plants. The SA oil petroleum value chain is initiated by the shipping of crude oil at refineries where it is processed into various value-added products. The final products are thereafter distributed to wholesalers and retailers throughout the supply chain network via various transport modes, which includes pipeline, road, and rail (KPMG, 2016). The value chain also comprises of both upstream and downstream activities. Upstream activities include exploration and production of crude oil, and downstream activities include refining processes, distribution, and marketing to the end-consumer (SAPIA, 2020). The production of refined petroleum products entails the refining of crude oil, transformation of coal-to-liquid fuels (CTL), as well as the transformation of gas-to-liquid fuels (GTL) (SAPIA, 2020). Sasol and Petro SA operate the CTL and GTL respectively, these refineries also known as referred to as synthetic refineries. The oil refineries are located across the country as depicted in Figure 29.

The crude oil supply chain consists of a variety of internationally traded crude oil, with the two dominant oil reference prices being the West Texas Intermediate (WTI) and the Brent crude oil (Caporin, Fontini, and Talebbeydokhti, 2019: 21). The trading of oil futures involves the traders agreeing to trade the oil benchmark (Brent crude or WTI) at a particular price at a fixed date in the future (Killian, 2022). Although the price of Brent crude oil is highly correlated to other oil price benchmarks around the world, the USA prices its crude oil with reference to WTI (Bøe,Jordal,Mikula and Molnár, 2019:341; and Scheitrum,Carter and Revoredo-Giha, 2018:2), while the Brent crude price is widely accepted as the official oil benchmark outside of the United States. The crude oil supply chain landscape, such as the one depicted in Figure 16, where each leg of product movement is linked through logistics practice (Lisitsa, 2019:5). Global oil and gas value chain is initiated by the exploration of the commodities which are then transported and stored to be further processed into various products based on market needs (Baru, 2019:34).

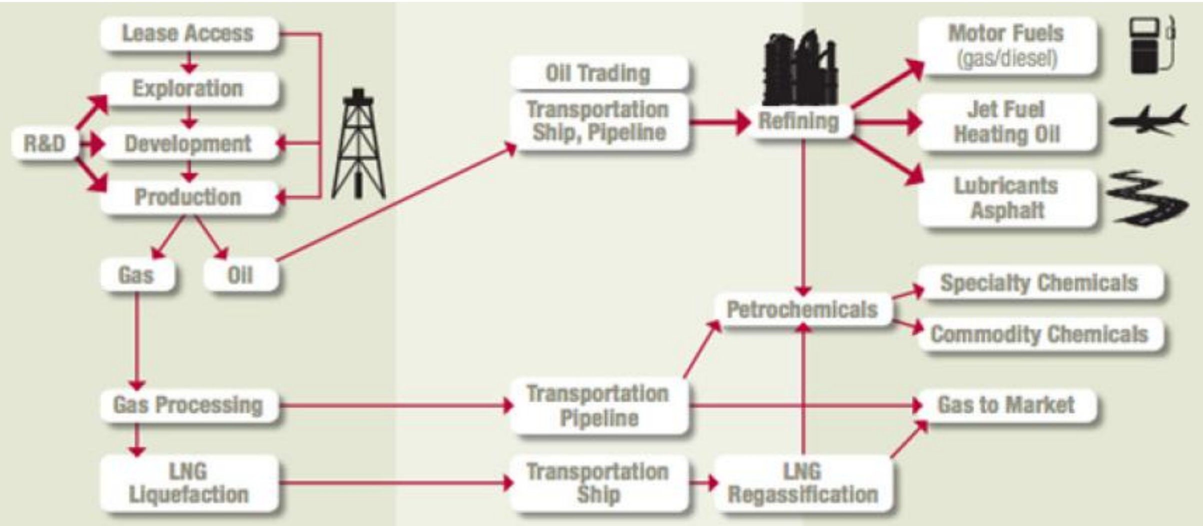

Figure 16: Global oil and gas value chain (Baru, 2019:34).

The price of oil has implications for both oil producing and oil consuming countries. Oil prices are negatively correlated with economic activities on both a macro and micro-level (Yang *et al*., 2002:107). The price of crude oil has implications on the economy of all countries as high oil prices are associated with increased inflation rates, which subsequently have a negative impact on economic activities (Yang, Hwang and Huang, 2002:107). The fluctuations of oil prices are significantly influenced by the Organization of the Petroleum Exporting Countries (OPEC) (Beck, 2019:1). The OPEC was founded by oil exporting countries, namely, Venezuela, Iran, Saudi Arabia, Kuwait, and Iraq in 1960 (Beck, 2019:1). The OPEC have the power to control the supply of crude oil among the member countries through distribution of production quotas, and this subsequently impacts crude oil prices (Beck, 2019:1). In 1973, the members of OPEC imposed an official ban on trade on Western countries and unilaterally set the prices of oil (Griffin and Teece, 2016:1). These actions displayed the political and economic power on the global economy that the OPEC has (Griffin and Teece, 2016:1). Following the embargo, the price of crude oil increased as a result of a low supply and high demand in the United States (Urbi, 2019).

Furthermore, according to the United States Energy Information Administration (EIA) drivers of oil markets, with regards to both price and production are: Geopolitical and economic events that affect market reaction in crude oil prices; World oil prices that move together due to arbitrage (Fernando, 2022), that is, the simultaneous purchasing and selling of the same asset in various markets with the aim of making a profit from the differences in the assets' listed price. In Figure 17 the various world oil prices are reproduced, while in Figure 18 depicts the crude oil prices versus the price of petrol (gasoline) in the US (in USD) (IEA, 2022).

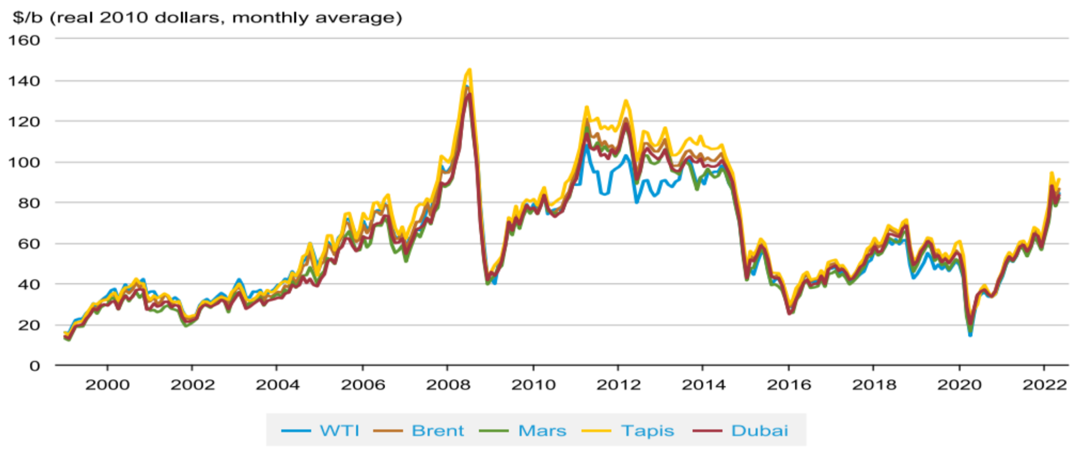

Figure 17: Movement of world oil prices (IEA, 2022).

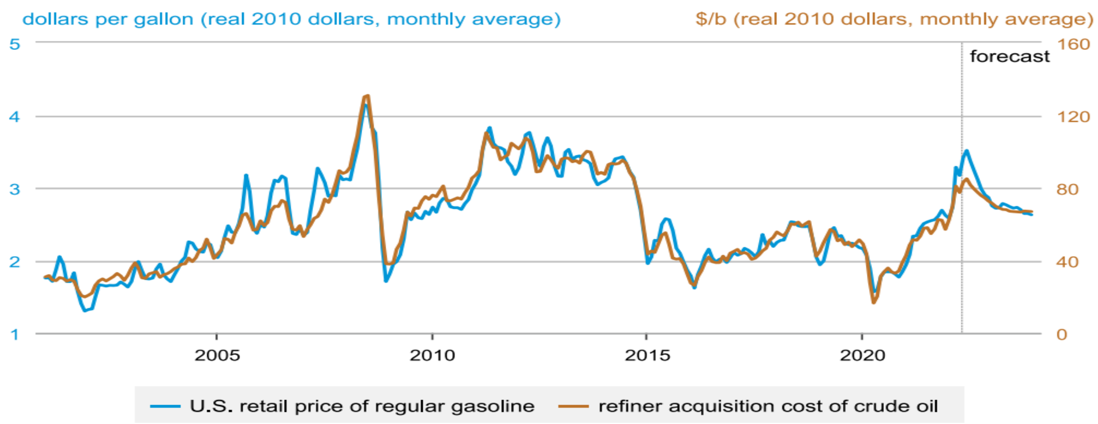

Figure 18: Crude oil price versus retail price of petroleum in the US (EIA, 2022).

Oil consumption is impacted by economic growth, see Figure 19 where we observe around 2009 and 2020 the world GDP was negative, and the consumption also was negative, but around 2021 we saw economic recovery. This can potentially be attributed to the fact that it is the period post-COVID-19 recovery period following vaccine rollouts and the relaxations of lockdown restriction, it is observed that the consumption and the worlds GDP growth recovered significantly. Oil consumption can also be influenced by variations in economic growth expectations, see Figure 20, where of particular interest is the negative growth (%) in 2020, followed by recovery in 2021.

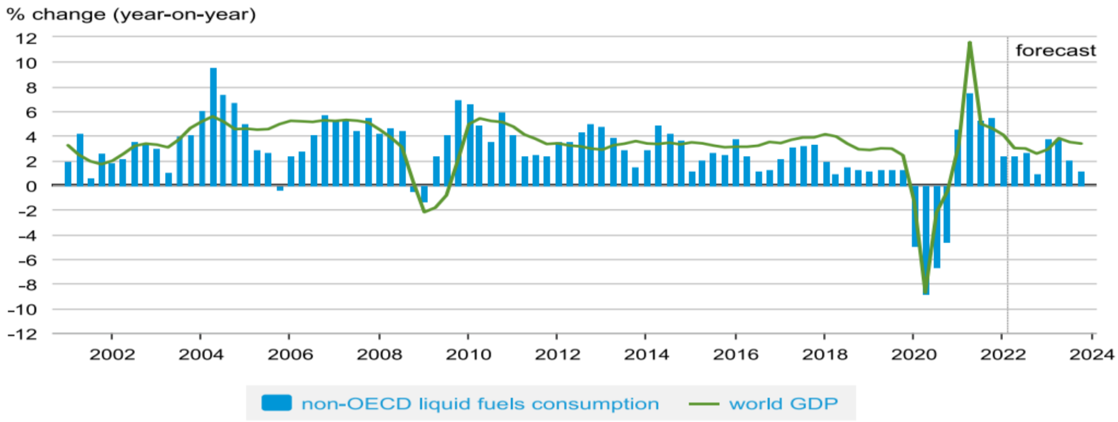

Figure 19: Oil consumption vs World Gross Domestic Product (GDP), (EIA, 2022).

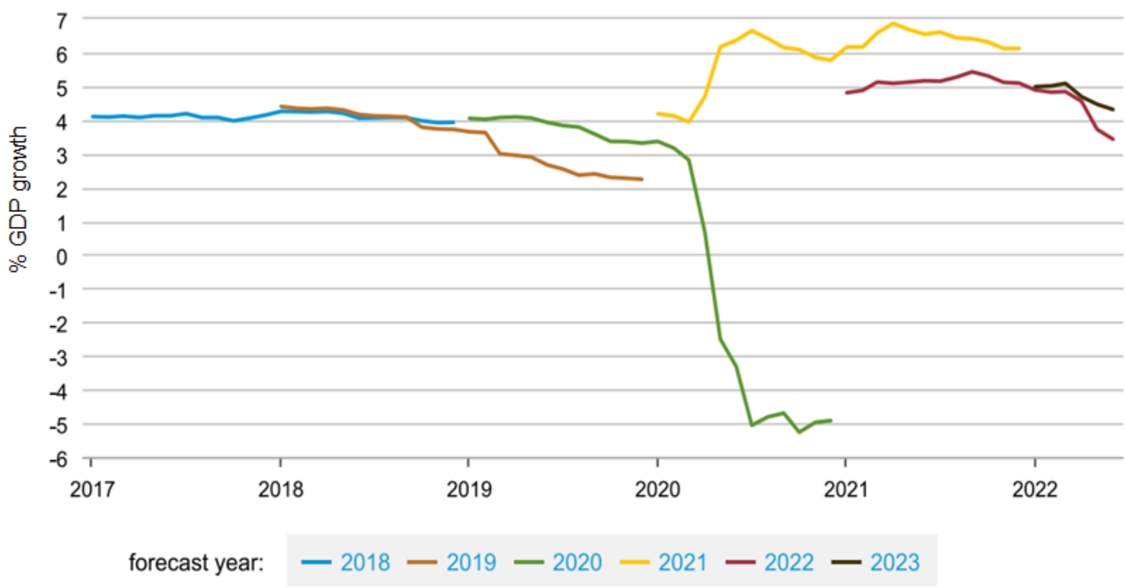

Figure 20: % growth in non-OECD countries (annual expectations), (EIA, 2022).

Oil price increases influence oil consumption in OECD countries, see Figure 21, with pronounced patterns in the post COVID-19 pandemic period starting around 2020.

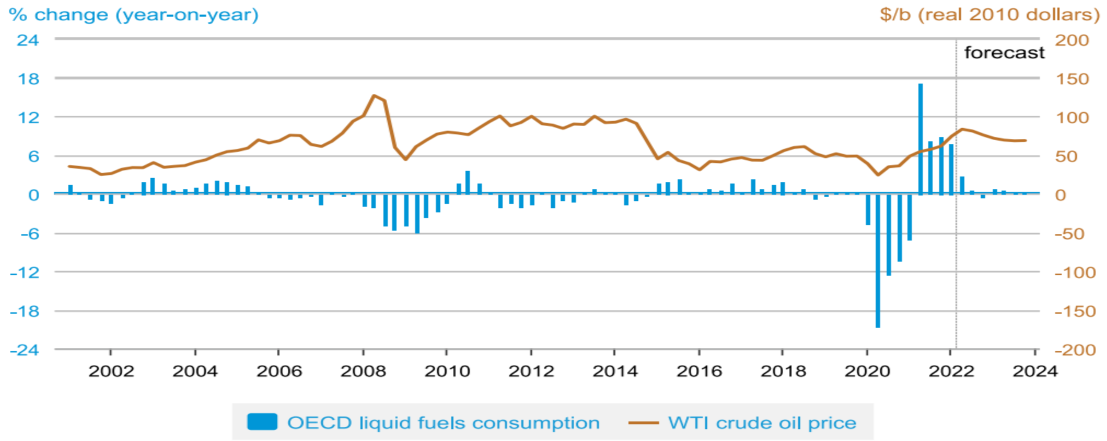

Figure 21: Crude oil price versus consumption in OECD countries (EIA, 2022).

Variations in non-OPEC production can also influence oil prices, see Figure 22; Non-OPEC supply outlook variations coincide with market sentiments, see Figure 23; Variations in Saudi-Arabia crude oil production influences oil prices, see Figure 24; Disruptions in supply tightens world oil markets and subsequently result in higher oil prices, see Figure 25.

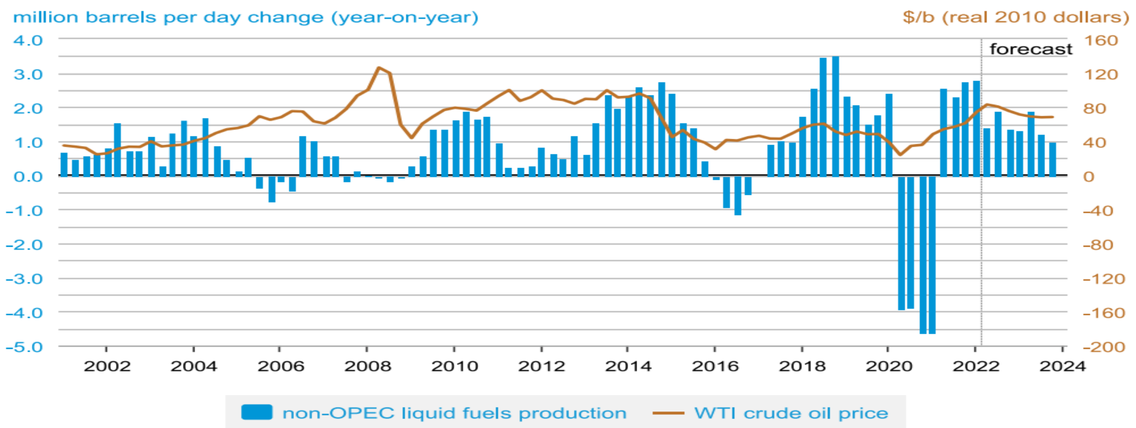

Figure 22: Changes in non-OPEC production versus affect oil prices (EIA, 2022).

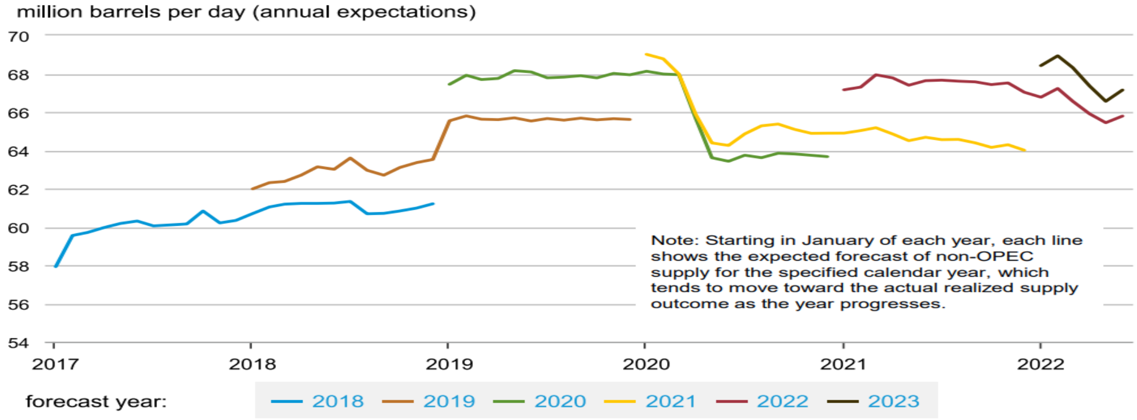

Figure 23: non-OPEC supply expectations (EIA, 2022).

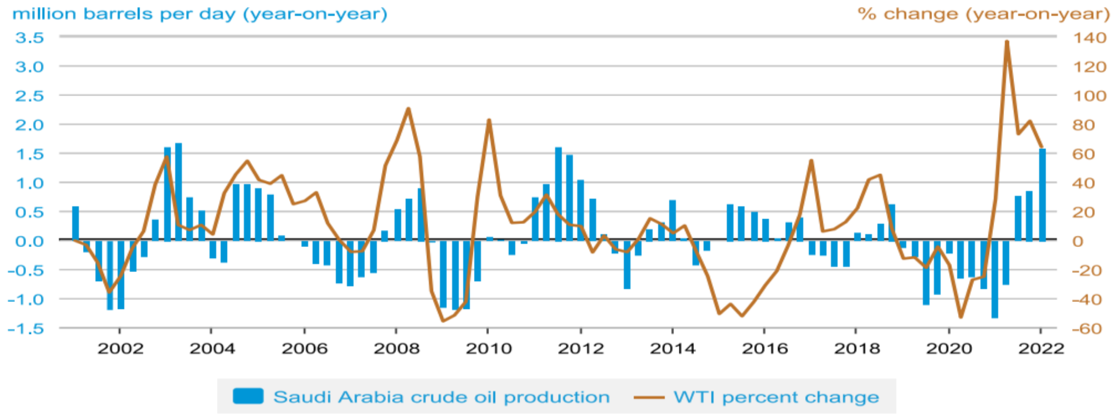

Figure 24: Changes in Saudi Arabia crude oil production versus oil prices (EIA, 2022).

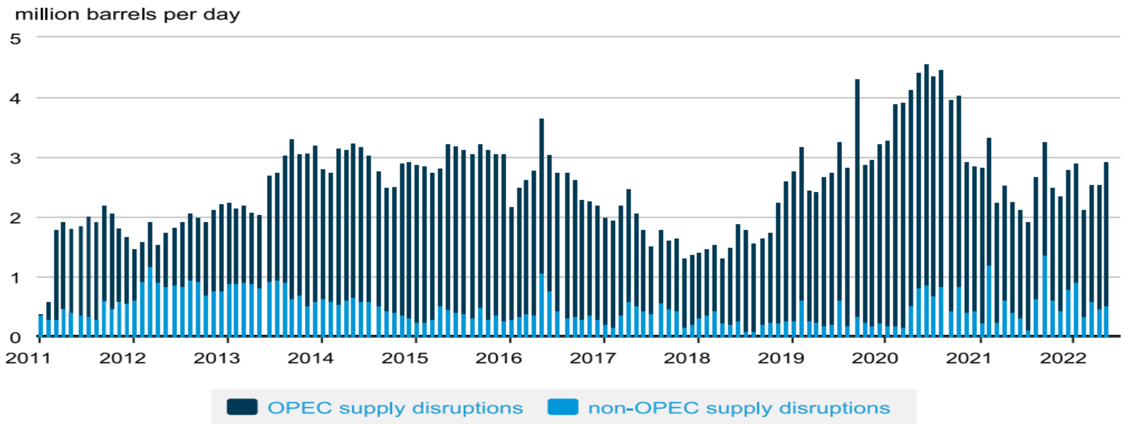

Figure 25: Unplanned supply disruptions (EIA, 2022).

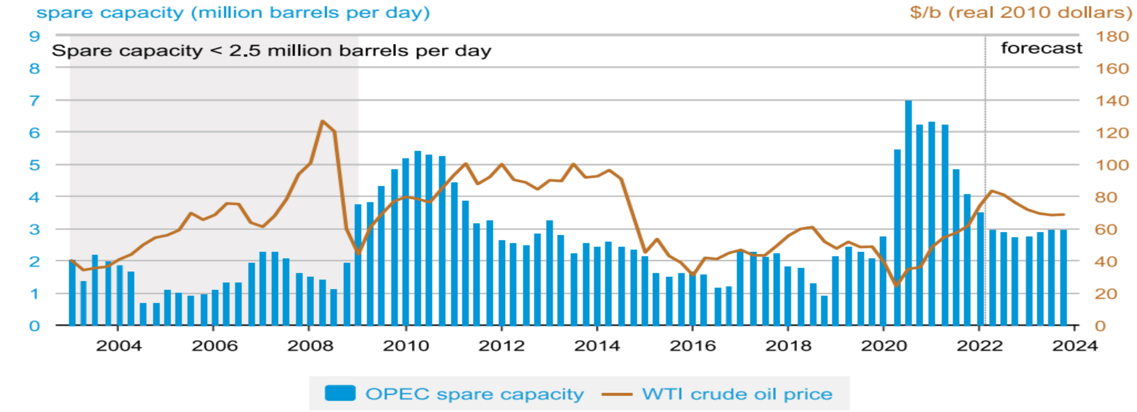

Figure 26: OPEC spare capacity versus oil price (EIA, 2022).

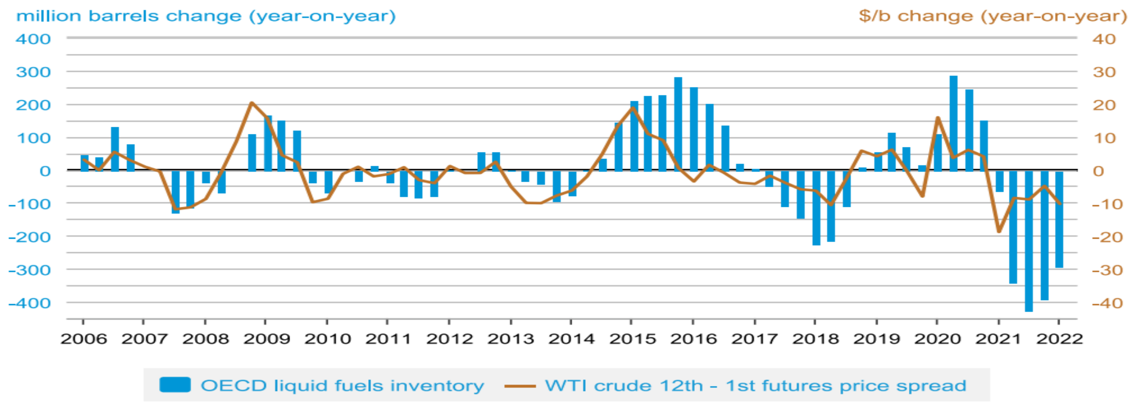

Figure 27: Inventory builds versus future oil prices (EIA, 2022).

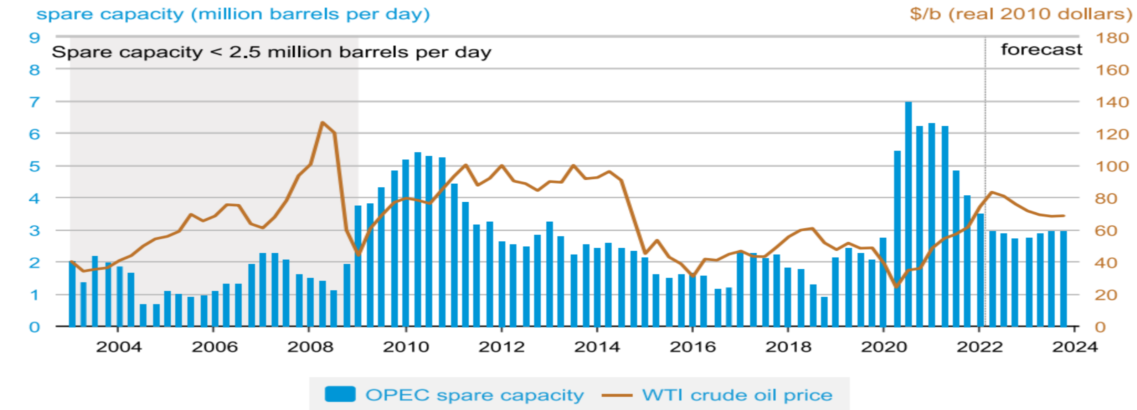

Figure 28: OPEC spare capacity versus oil price (EIA, 2022).

OPEC's production levels influence the ability to respond to demand and the inability to meet demand ultimately causes the increase of oil prices, see Figure 26; Inventory builds run parallel to increases in future oil prices relative to current prices (and vice versa), see Figure 27. Oil prices also fluctuate in response to OPEC spare capacity, see Figure 28.

4.1 South African Petroleum Market

The petroleum market in South Africa comprises of various refined products, with the foremost petroleum products sold in South Africa being petrol, diesel, jet fuel, illuminating paraffin, fuel oil, bitumen and liquefied petroleum gas (LPG), with main refineries spread across the coast as well as inland (Figure 30). Of these refined products produced, petrol and diesel are the major liquid fuels that are consumed in the country. According to the South African Department of Energy (DoE), 86% of the petroleum products sales comprised of petrol (36%) and diesel (43%) in 2019 (DoE, 2020). The focus on this investigation will only focus on petrol and diesel.

Figure 29: Map showing location of refineries in South Africa (SAPIA, 2020).

According to SAPIA (2020) there are about 4,600 petroleum retail outlets in South Africa, with the major players being BP Southern Africa, Chevron South Africa, Engen Petroleum, PetroSA, Sasol Oil, Shell South Africa and Total South Africa. The South African petrol market currently comprises of two grades and differentiated based on the levels of octane which they contain. The unleaded petrol options that are currently available are Unleaded Petrol (ULP)-93 and ULP-95. The manufacturers of cars normally recommend the best type of petrol that is suitable for their car models. It has been reported that there is not much of a difference between 93-octane and 95-unleaded petrol. The price of 93-Octane is however lower of the two options, and this is because it contains fewer amounts of flammable hydrocarbon substance. 95-Unleaded is recommended for drivers who travel long distances as it has a higher compression peak and enables an increase to the car's engine performance (Sicetsha, 2020).

Diesel is distilled from crude oil and, like petrol, it can be categorised into various grades. The use of diesel spans across industries and includes motor vehicles, mining and agriculture. However, the increased awareness of climate change has called for diesel that has low sulphur content. The sulphur content in diesel is measured using the unit "parts per million" (ppm), so the greater the greater the sulphur content the greater ppm. Standard diesel contains 500ppm, low sulphur diesel contains 50ppm and ultra-low sulphur diesel has a minimal sulphur content of between 15- and 10-ppm (SAOil, 2019). Prior to the introduction of the lower sulphur diesel products, which are referred to as "Automotive Diesel 50" and "Automotive Diesel 500" in the data collected herein, was the use of regular diesel with high sulphur content, referred to as Automotive Diesel in the data collected. Data obtained from SAPIA differentiates between the different grades of petrol while the data obtained from DoE aggregates all diesel grades per quarter.

South Africa's petroleum consumption landscape is driven by the consumption of petrol and diesel, where the price of petrol is regulated by the government. The retail industry accounts for most of the petrol consumption, while diesel is mostly consumed in the country's commercial sector. A prominent commercial consumer of diesel is Eskom (electricity supplying state owned entity), who use fuel oil as an alternative to coal to power their stations and diesel to power their open-cycle gas turbines. Fuel oil, also referred to as furnace oil, comprises predominantly of residues from crude oil distillation and its primarily used for steam boilers in power plants, aboard ships, and in industrial plants.

South Africa's petrol and diesel consumptions were reported by the South African Petroleum Industry Association (SAPIA) from 1987 to 2005. The data was reported on a monthly frequency and comprised of leaded petrol grades which were eventually phased out by 2005. Unleaded petrol data ranges from 2005 onwards and is reported by the DoE on a quarterly basis. Similarly, diesel consumption data was reported by SAPIA from 1987 to 2005 at a monthly frequency and is now reported by the DoE on a quarterly basis.

4.2 South African Price and Consumption Forecast Literature

Literature focusing on South Africa's crude oil landscape mostly focuses on the role of crude oil prices in forecasting other variables of interest such as interest rates (Gupta and Kotze, 2017) and stock returns (Gupta and Modise, 2013), to name a few. Internationally, topics such as: the evaluation of the predictive impact of geopolitical risk on crude oil price volatility are of focus (Nonejad, 2022); The construction of a stock-price forecast convolutional neural networks (CNN) model using gold and crude oil indicators (Chen and Huang, 2021); and the novel approach of using online media sources to forecast the crude oil price (Elshendy *et al*., 2018).

In general, international crude oil consumption forecasting literature is dominated by the investigation of various forecasting models. Yu, Zhao, Tang and Yang (2019:213 - 223) in their study used Google Trends as an online big data source to propose a novel forecasting model for oil consumption, using the key words: "oil price", "oil consumption” and “oil inventory” and the selection of keywords was informed by existing studies on oil markets. Limitations of the study, as acknowledged by the authors, include the lack of a comprehensive investigation of the oil market to identify other variables that could have an influence on the proposed model (Yu *et al*., 2019:10). In another study a forecasting model based on online media text mining is proposed where the proposed methodology attempts to apply deep learning techniques to crude oil forecasting (Li, Shang and Wang, 2019). Another study proposes a prediction methodology where Google Trends and online media text mining are combined. Interestingly, the experimental results suggested that the author’s proposed text-based and online-big-data-based forecasting methods outperform other techniques (Wu *et al*.,2021). Olayiwola *et. al*. (2020) used time series analysis for statistically forecasting petrol price in South Africa. Their study data comprised of retail fuel data ranging from 2000–2013 which was sourced from the Department of Energy (DoE). Time series plots and analysis were used in the methodology from which they noted that petrol price and consumption has an upward trend. Measures of accuracy were computed for each method of analysis (Olayiwola *et. al*.,2020). Madhubhashitha and Appuhamy (2022) focused on determining the prediction accuracy of time series and deep learning neural network model to forecast the daily Platts price per barrel of diesel. The researchers concluded the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) as opposed to the Long Short-term Memory (LSTM) neural network method was more appropriate.

Existing petrol consumption prediction literature focuses on predicting general petroleum product consumption, predominantly in the context of the transportation industry (Shafee et al., 2004; and Chłopek and Waśkiewicz, 2013). Much like petrol consumption prediction literature, majority of diesel consumption prediction literature focuses on predicting the consumption of diesel in the transportation sector (Eder and Nemov, 2017), and forecasting diesel consumption in relation to greenhouse gas emissions (Trofimenko *et al*., 2020). Petrol consumption literature generally focuses on investigating factors that affect consumption, such as, customer preference determinants that improve the competitive edge of petrol stations (Manneh *et al*., 2020). The increasing drive towards a greener supply chain has also sparked the interest of scholars to investigate green hydrogen as an alternative to petroleum products (Thapa *et al*., 2021 and Xiang *et al*., 2021).

Since the overarching pursuit in this thesis is to integrate insights from relevant customer data to inform supply chain decision making, and enhance supply chain agility, with particular focus on the petroleum sector, in this chapter, we proceed to develop a petrol and diesel consumption statistical model using a set of set of domestic and global customer-business indices, along with a set of domestic macro-economic indicators, which will elaborated on below.

Petrochemicals companies invest significant amounts of capital in business intelligence tools which generate various data that supply chain personnel translate into insight using various tools such as SCA. These insights are typically used to inform tactical supply chain decision-making which is usually reactive in nature. The current link between strategic and tactical supply chain in this environment is characterised by sales targets as opposed clear strategic objectives that are driven by predictive models which can enable improved decision-making on a tactical level. The accurate prediction of oil consumption thereof is key for not only policy making (Li, Wang, Wang, and Li, 2018), but also for the supply chain sustainability. The ability to meet customer demand is driven by supply chain agility and the ability to anticipate customer needs. The following section of the thesis aims to motivate the choice of potential variables for the prediction of both petrol and diesel consumption in South Africa.

4.3 Motivation for the Selection of Variables for the Prediction of Consumption Petrol and Diesel Consumption

For this prediction exercise, the thesis focuses on two such domestic indicators, namely, the Consumer Confidence Index (CCI) and the Business Confidence Index (BCI) indicators, to investigate how customer and business sentiment data can provide potential insights for general strategic supply chain decisions, and with respect to petroleum demand in South Africa. The CCI and BCI are based on customer and business sentiment surveys, that are inherently purposed to provide insights into individual and commercial economic activity outlook. The South African CCI and BCI surveys are conducted by the Bureau of Economic Research (BER), which are made available on a quarterly basis. Both the indicators are discussed below in detail.

To calculate the CCI, three questions are posed to adults who are living in South African urban areas, and inquires on the anticipated performance of the economy, the anticipated financial status of households, and the perceived rating of the appropriateness of the current time to buy long-lasting goods such as furniture, appliances and electronic equipment (BER, 2020). The index is expressed as a net balance and is expressed as percentage of respondent expecting an improvement / the appropriate time to purchase durable goods less the percentage anticipating a deterioration / bad time to purchase durable goods. The BER CCI can vary between -100 and +100. Since 1982 when the BER started publishing the index, the index has oscillated between -33 (which indicates an acute lack of confidence) and +23 (which indicates extreme confidence). The CCI value of +2 is assumed as the neutral level as it is the average of the index (BER, 2020). A low confidence indicates that consumers are in frame of mind that will result in them likely minimising their spending on necessities such as food or services, while they redirect their income to debt repayment obligations (Kershoff, 2000:8). A high confidence indicates the opposite consumer state of mind and indicates a likelihood that they incur debt or reduce savings while increasing their spend on discretionary items (Kershoff, 2000:8). This includes spending on items such as furniture and motor vehicles and assumes that these items are often financed through credit (Kershoff, 2000:8). BER provide the data at a quarterly frequency and is available from 1982:Q2 to 2022:Q1 at the time of this investigation.

The CCI is affected by various macroeconomic factors. Despite their financial position, consumers are inclined to spend when they are confident about economic conditions, which includes their perception about their own finances (Maverick, 2020).

Employment levels are believed to be among the variables that impact on consumer confidence (Bremmer, 2008:4). People who receive a steady income are more likely to spend money on discretionary items. The increase of wages also insinuates a greater likelihood for consumers to spend on discretionary items. Thus, the unemployment rate can be considered as an economic indicator that can be considered to give hint to consumer demand for goods (Maverick, 2020). However, factors such as family responsibilities also inform the decisions taken by consumers on which items to spend money on. Another variable to consider is the inflation rate. Higher inflation rates decrease the likelihood for excess income after the payment of essentials. (Maverick, 2020). Inflation is an economic term that has an implication on consumer purchasing power. The existence of inflation results a reduction in consumer buying power over time. In addition to the above-mentioned variables, Li and Lin (2015:28) in their study, present empirical evidence that price of crude oil is negatively related to consumer spending. The authors assert that domestic consumption is impacted by high oil prices which decrease discretionary income while also causing an increase in the prices of other consumer goods and services (Li and Lin, 2015:21).

The BCI is the unweighted mean of five sectoral indices, namely that of manufactures, building contractors, retailers, wholesalers and new vehicle dealers. The index ranges between 0 and 100, where 0 indicates an extreme lack of business confidence, 50 represents neutrality and 100 represents extreme confidence. The BER BCI survey uses deliberate sampling. and its selection options are: “up”; “remain the same”; or “down” compared to a year ago. Results are calculated based on sector weights and a net balance value is obtained. The building and construction sector sample population comprises of Architects, Quantity surveyors, Residential & non-residential contractors, Residential & non-residential sub-contractors, and Civil engineering contractors. The manufacturing sector sampling population comprises of Quarterly Manufacturing Surveys and the Purchasing Manager Index (PMI) report is also considered. In the internal trade sector, a retail survey is conducted which encompasses both retail and wholesale respondents and new vehicle dealers. The Financial Services sector data comprise of web-based reports and respondents from Retail banks, Merchant & Investment banks, Investment managers, Life insurers and Short-term insurers. Lastly, other services that are considered in the index are catering and accommodation, transport, storage and communication, real estate and business services and personal services (Federal Reserve Bank of New York, 2022). The significant positive relationship between the indicator and actual economic activity renders the indicator as valuable information about current and future economic developments (Binge, 2020).

The final supply chain indicator that is of interest in this chapter is a global indicator, namely, the Global Chain Pressure Index (GSCPI), which was sourced from the Federal Reserve Bank of New York website[2]. The aim of the GSCPI is to provide a comprehensive summary of potential supply chain disruptions by integrating commonly used metrics and comprises of the following indices: the Baltic Dry Index (BDI) and Harpex Index for measuring transportation costs; indices provided by the United States (US) Bureau of Labour Statistics which measures freight costs; and various components from the Purchasing Manufacturing Index (PMI) surveys with specific focus on manufacturing economies, namely, China, the Euro area, Japan, South Korea, Taiwan, the United Kingdom and US (Federal Reserve Bank of New York, 2022). While there are various measures to proxy the integration of financial markets and trade, the GSCPI provides a novel measure to capture the status of global supply chains, which is a critical aspect of modern product processes (Benigno *et al.*, 2022). A low GSCPI indicates that the globalisation of supply chains while and high index value indicates a deglobalisation of supply chains in response to supply chain disruptions.

The final two predictor variables of interest are related to the domestic macro-economy, namely: the price of Brent crude oil in ZAR currency, and the SA Gross Domestic Product (GDP). The Brent crude oil price in ZAR is calculated using the price of Brent crude oil (in US dollars per barrel) sourced online from United States Energy Information Administration, and the Rand (ZAR) to Dollar (USD) Exchange Rate. This is done because oil importing countries, like South Africa, are subject to the impact of the exchange rate volatility. The cost to produce oil related goods and

[2] Available: https://www.newyorkfed.org/research/gscpi.html.

services generally increases with increasing Rand to Dollar prices. Fluctuations in the Dollar exchange rate affects the price of oil since majority of oil trading invoices in international markets are expressed in Dollars (Mensah, Obi, and Bokpin, 2017). The reader is reminded that the thesis uses Brent crude price as this is widely accepted as the official oil benchmark outside of the United States.

The second domestic indicator is the Gross Domestic Product (GDP) which measures a country's income and output and equates to the sum of expenditures of all final goods and services that have been produced within the country during a stipulated time period (Schoeman, 2021). There exist various methods to measure a country's economic growth, of which the real domestic product (GDP) is commonly used. The GDP number is expressed in terms of the worth of the of a country in local currency.

The hypotheses of interest are therefore the following for both petrol and diesel consumption, individually:

i. H1: CCI has a positive effect on petrol/diesel consumption
ii. H2: BCI has a positive effect on petrol/diesel consumption
iii. H3: GSCPI has a negative effect on petrol/diesel consumption
iv. Brent (ZAR) has a negative effect on petrol/diesel consumption
v. H4: SA GDP has a positive effect on petrol/diesel consumption.

4.4 Methodology

The approach to the investigation in this chapter will following the following route: first the visual time series for the two dependent variables of interest is presented, namely the petrol and diesel volume consumption, both in its original units (million litres) and the corresponding seasonally adjusted series. Visual plots of the independent variables of interest are presented, namely, the CCI, BCI, GSCPI, the price of Brent crude (in ZAR) and SA GDP. An exploratory analysis is then conducted via bivariate correlation plots between the each of the independent variables and each of the dependent variables, both for the full sample (1998:Q1 to 2021:Q4) and for the pre-COVID-19 period (ending 2019:Q4). Finally, with the aim of the chapter exercise being to quantify the role of the two confidence indices (CCI and BCI) in predicting the two volume consumptions (the petrol and diesel), along with the other drivers of interest (namely GSCPI, the SA GDP and the price of Brent crude (in ZAR)), a simple linear regression model is evaluated, followed by the multiple linear regression model, for both the full sample, and the pre-COVID-19. Each of these methods, namely, seasonal adjustment, de-trending, correlation, and the predictive linear regression, are described briefly below, with the corresponding data and results presented in the sections 4.5 and 4.6 respectively.

4.4.1 Correcting for Seasonality and De-trending

Since the variables of interest are quarterly volume sales (million litres) for both petrol and diesel, it is expected that there will be an element of seasonality as well as possible trend in the series. The United States Census Bureau's X-13ARIMA-SEATS3 seasonal adjustment method is used to seasonally adjust both the petrol and diesel series, implemented in EViews®. The X-13ARIMA-SEATS program is a seasonal adjustment program, an improvement on the previous version of X-11 Variant of the Census Method II seasonal adjustment program. Improvements to the model include and increasingly self-explanatory and adaptable user interface with numerous new diagnostics that enable the user to detect and resolve inadequacies in the seasonal and calendar effect adjustments that are obtained under the selected program options (United States Census Bureau, 2017). Two methods are generally applied in X-13ARIMA-SEATS to perform seasonal adjustment: either by using an ARIMA model-based seasonal adjustment as in SEATS or using an enhanced X-11 method. X-13ARIMA-SEATS makes use of standard seasonal ARIMA model notation, where: (p, d, q) $(P, D\ Q)$s refers to the seasonal autoregressive, differencing, and moving average orders respectively (United States Census Bureau, 2017).

[3] https://www.census.gov/data/software/x13as.html

When performing seasonal adjustment, the program does not separate the long-term trend from the cycle because these two components of the time series are usually too short to perform a reliable estimation. Two algorithms for decomposition are offered by X-13ARIMA-SEATS: SEATS and X-11. The decomposition of a series in the X-11 algorithm is conducted by means of linear filters, and in both methodologies, deterministic effects to the stochastic components are derived by assigning deterministic effects (Maravall, 2009). The independent variables are not seasonally adjusted.

To de-trend the series, the following approach is used: Let x_t be the original time series at time t, and let y_t be the de-trended time series at time t, then :

Equation 1: De-trending time series

$$y_t = ((ln\, ln\, (x_t)\ -ln\, ln\, (x_{t-1})\,) \times 100.$$

The three indices' series are not detrended, namely: CCI, BCI and GSCPI. All the regression models are estimated using ordinary least squares (OLS) and evaluated in EView® package.

4.4.2 Correlation Analysis

Correlation measures the linear dependency between two variables and its values range between -1 and 1. A positive correlation is observed when variables move in tandem, whether in a positive or negative direction. A real-life illustration of a positive autocorrelation could be the increase of car sales that subsequently results in the increase of fuel demand (Hayes, 2020). Conversely, negatively correlation variables move in opposite directions. It is computed as follows for random variables X and Y (Marco, 2021):

Equation 1: Correlation analysis

$$corr[X, Y] = \frac{Cov[X, Y]}{stdev[X]stdev[Y]}$$

where:

- $Cov[X, Y]$ is the covariance between the random variables
- $stdev[X]$ and $stdev[Y]$ are the standard deviations X and Y

Linear association between the variables of interest is assumed, particularly between each of the two dependent variables, and the independent variables. A correlation analysis is performed for petrol and diesel consumption (growth%) in terms of CCI, BCI, GSCPI, GDP and the Brent crude price (in ZAR).

4.4.3 Predictive Linear Regression

To predict both petrol and diesel volume consumption the following the predictive multiple linear regression approach is proposed:

Equation 2: Predictive multiple linear regression

$$Y_i = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p + e_i$$

where: i= 1, 2, …, n; Y is the dependent variable; $\boldsymbol{X}$ is the set of independent variables; β_0 is is referred to as the intercept; $\beta_i s$ are the slopes; finally, e_i is an independent error term which is identically distributed with a Gaussian distribution with mean 0 and variance σ^2 (Zou *et al*., 2003). It is implicit here that when there is only one independent variable, this converts to the usual simple linear regression. The estimated or sample regression function is denoted as follows (Stewart, 2016):

Equation 3: Estimated or sample regression function

$$\hat{r}(X_i) = \hat{Y}_i = \hat{\beta}_0 + \widehat{\boldsymbol{\beta}}' \quad \boldsymbol{X_i}$$

where: $\hat{r}$ is the estimated or sample regression of the observed variable X_i, $\hat{\beta}_0$ and $\widehat{\boldsymbol{\beta}}$ are the estimated intercept and slope vectors based on the sample, and $\hat{Y}_i$ is the fitted/predicted value. The function also consists of residuals which can be thought of as the prediction errors of the model estimates:

Equation 4:Prediction error

$$\hat{u}_i = Y_i - \hat{Y}_i$$

Where $\hat{u}_i$ is the prediction error and $Y_i - \hat{Y}_i$ are the differences between the true value and predicted values, respectively (Stewart, 2016).

Ordinary Least Squares (OLS) involves the estimation of parameters in a regression model, where the sum of the squared residuals is minimised. Using this methodology, a line arrived at that goes through the data points that best minimise the sum of the squared differences between the observed values and corresponding fitted values (Frost, 2021). It is statistically expressed as follows (Stewart, 2016):

Equation 5: Ordinary Least Squares

$$(\hat{\beta}_0, \hat{\beta}_1) = arg_{b_0,b_1} min \sum_{i=1}^{n} (Y_i - \beta_0 - \beta_1 X_{i1} - \cdots - \beta_p X_{ip})^2.$$

4.5 Data

The data used in this examination starts from 1998:Q1, particularly because that is from when the GSCPI is available, and the end period is 2021:Q4. This period also includes the disruptive period beyond 2019:Q4 when the economics and supply chain dynamics were both domestically and internationally affected due to the COVID-19 pandemic. The visualisation of both the series of interests is presented below, namely petrol and diesel consumption (in million litres), and then the corresponding seasonally adjusted (using X-13ARIMA-SEATS Seasonal Adjustment method), and then further the corresponding de-trended growth percentage series.

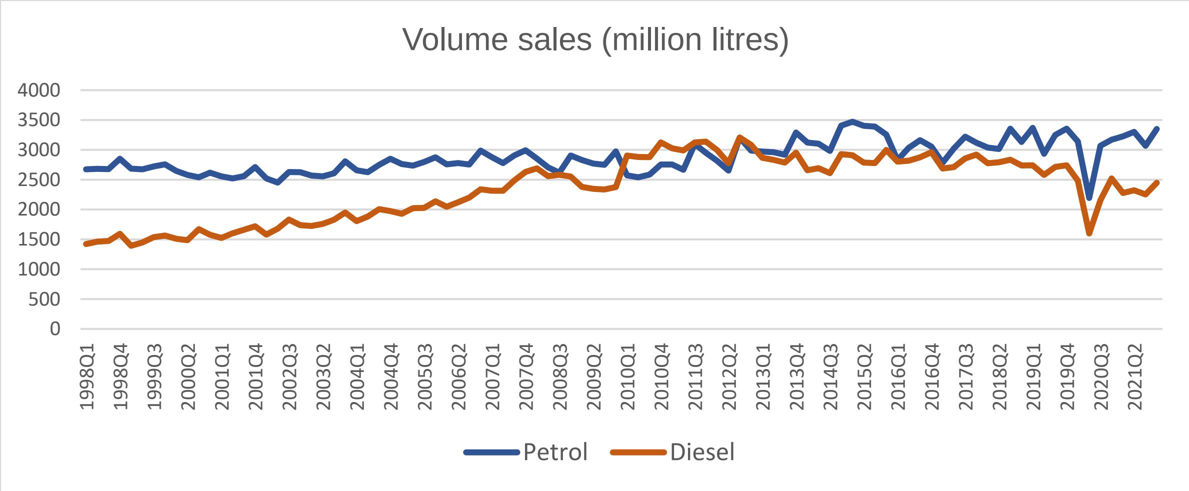

Figure 30: South Africa's petrol and diesel historical sales.

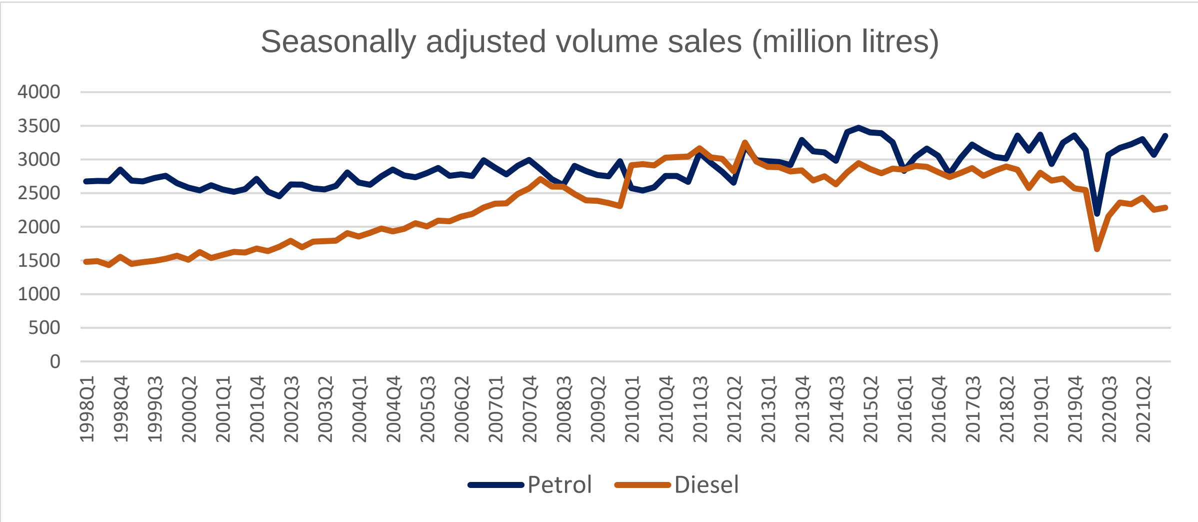

Figure 31: Seasonally adjusted petrol and diesel volumes sales.

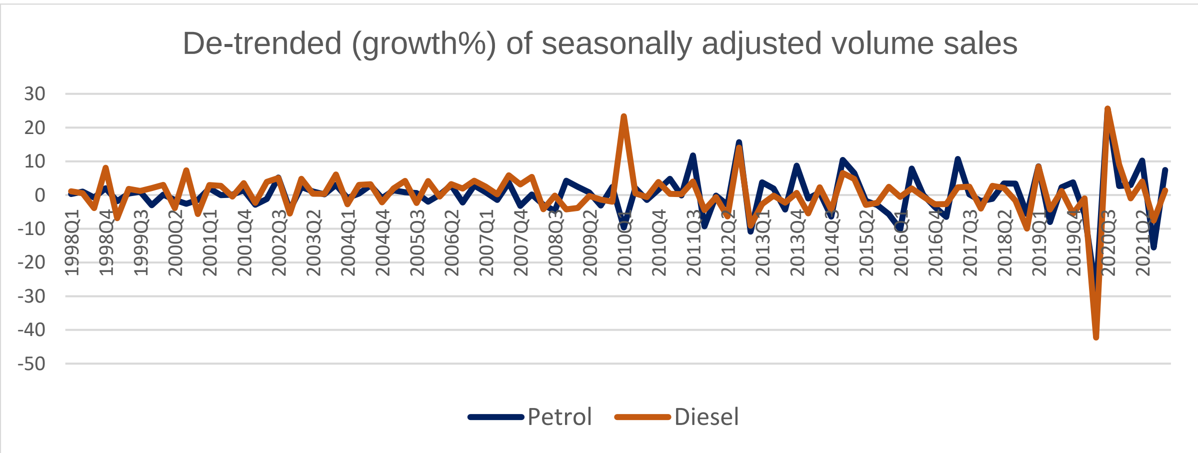

Figure 32: Detrended (growth%) of seasonally adjusted volume sales.

Until 2009:Q1, the seasonally adjusted and de-trended (growth) series for both petrol and diesel consumption were within the (-10, 10) band. In 2010:Q1 the first breach of a growth in diesel consumption (%) greater than 20, a period that coincided with the FIFA World cup in South Africa. The region post 2019:Q4, which is the region since the COVID-19 pandemic, shows major negative growth (below -10%) and then recovers.

Next, the visualisation of the two indices of particular interest in this chapter is presented, namely the CCI and the BCI. Both the series appear correlated visually, as well as statistically (0.6) as seen in the correlation table presented below.

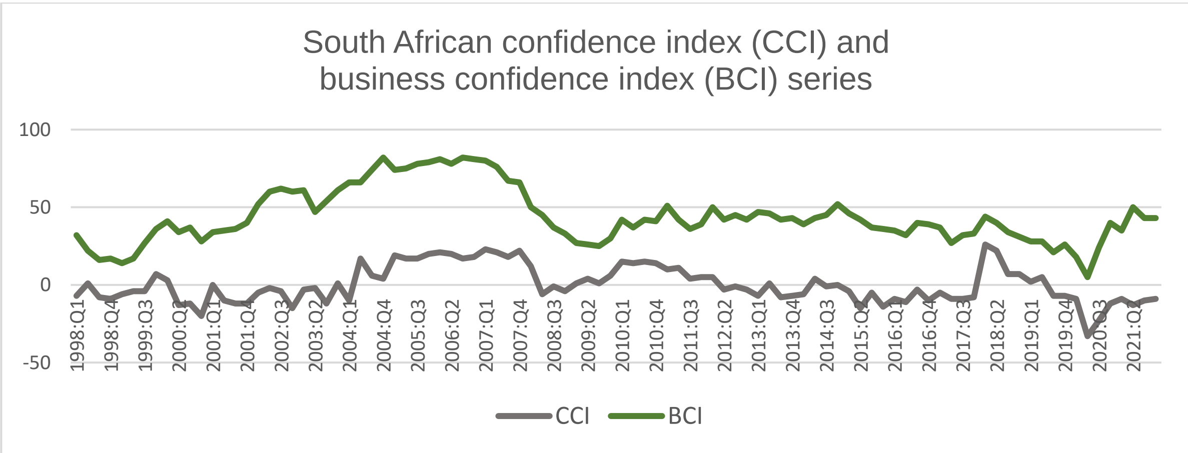

Figure 33:South Africa's Consumer Confidence Index (CCI) and Business Confidence Index (BCI).

Next, the GSCPI index is presented and was obtained by converting the monthly series as published, into quarterly average. The GSCPI series presents the index for the global supply chain conditions, with lower values informing conducive conditions, and the higher values informing that the conditions were disruptive to global trade. We see from the GSCPI graph that post 2019:Q1 the conditions never recovered, and in fact remained highest during this study period.

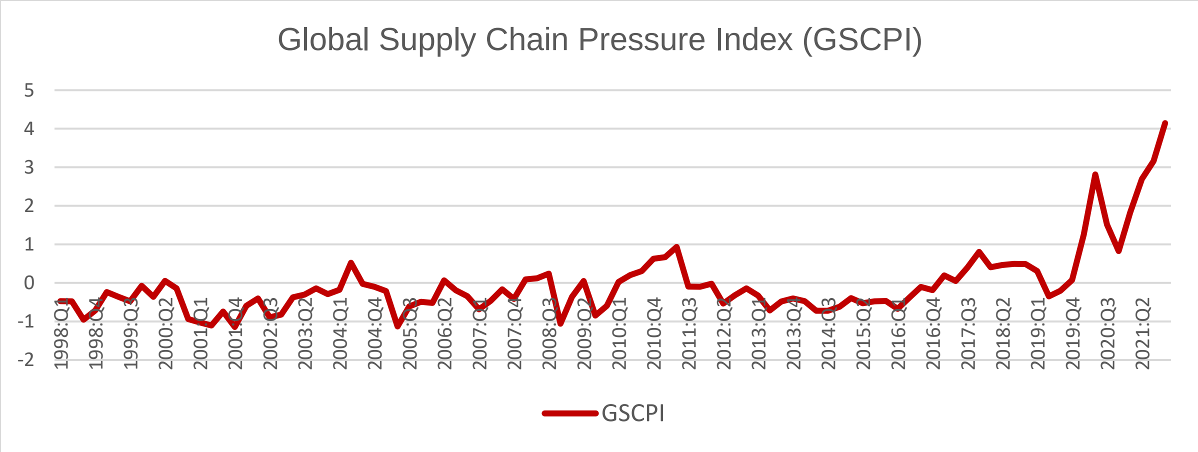

Figure 34: Global Supply Chain Index (GSCPI).

Finally, the visualisation of the South African Gross Domestic Product (GDP) and the price of Brent per barrel in SA Rand (ZAR) value are presented, with latter being derived by multiplying the international price of Brent crude per barrel (in USD) with the corresponding Rand-Dollar exchange rate in that period.

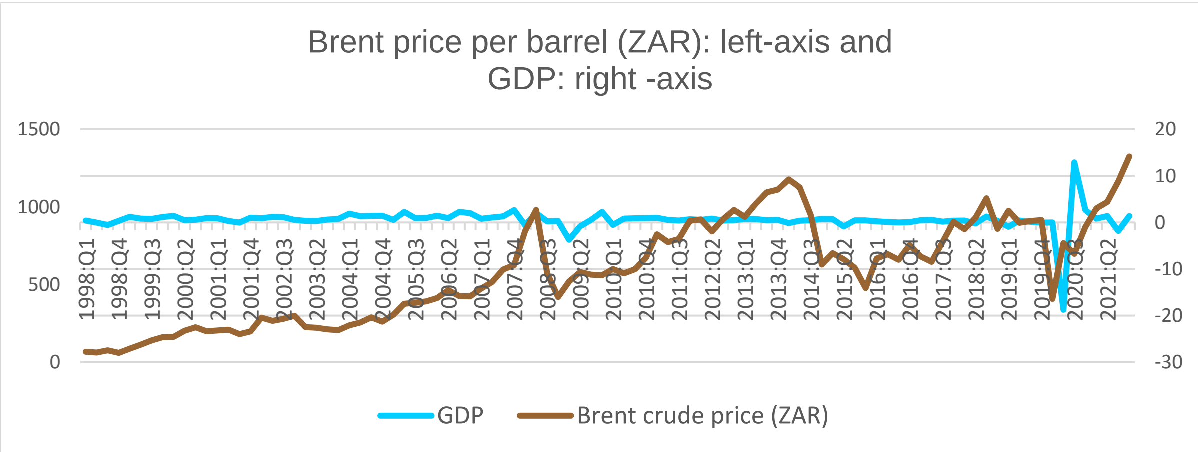

Figure 35: Brent price per barrel and GDP.

Below, the SA GDP and Brent (in ZAR) growth (in percent), which are the corresponding de-trended series from the raw corresponding data. Recall that to de-trend the series the following equation was applied:

Equation 6: De-trending time series

$$y_t = ((ln\ ln\ (x_t)\ -ln\ ln\ (x_{t-1})\ ) \times 100.$$

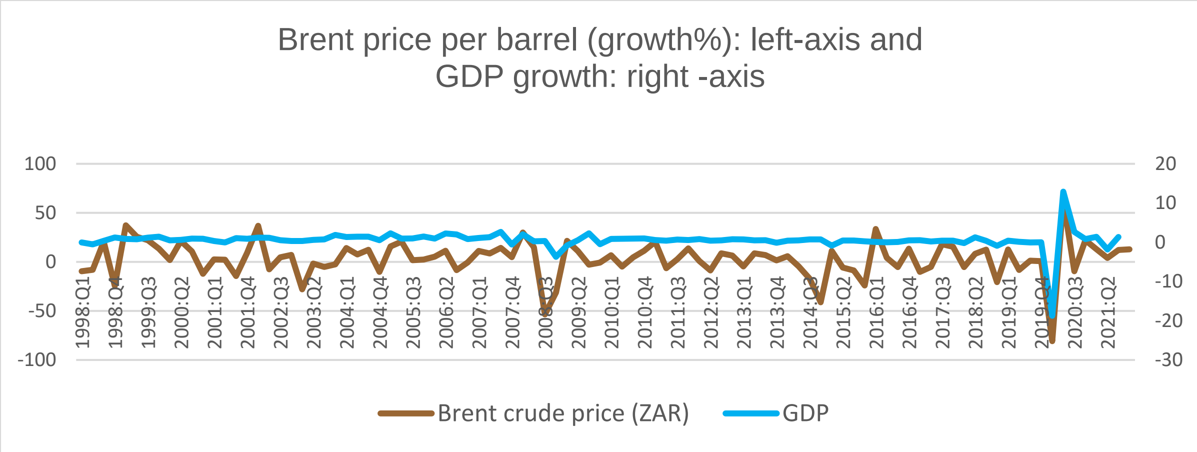

Figure 36: Brent price per barrel (growth%) and GDP growth.

The price of Brent saw a sharp decline during what was termed the 'Great Recession' between 2007 and 2009. While the economic downturn which originated in the USA, it had an impact on markets globally. In 2014, the oil price dropped fundamentally due to an oversupply of petroleum compared to demand. 2021: Q1 shows falling oil prices as a result of COVID-19 and the associated demand. While South Africa's GDP has remained stable over the observed period, the impact of COVID-19 is notable in 2020:Q1. Recent data indicates that SA's economy has however reached pre-pandemic levels and the real GDP is slightly higher than prior the pandemic (Statistics South Africa, 2022).

4.5.1 Correlation and Corresponding Plots for the Full Sample

It is reminded to the reader that the full-sample is the period 1998:Q1 to 2022:Q4 and is inclusive of the post-COVID-19 period from 2020:Q1.

Table 7: Full sample correlation.

Consumption (growth%)	Full Sample (1998:Q1-2022:Q4)				
	CCI	BCI	GSCPI	GDP	Brent crude price
Petrol	0.069	0.097	-0.067	0.615	-0.157
Diesel	0.271	0.229	-0.159	0.717	-0.216

In following figures, the full-sample correlations between petrol (Figures 38-42), and similarly for diesel (Figures 43-47), with the five independent variables of interest are presented.

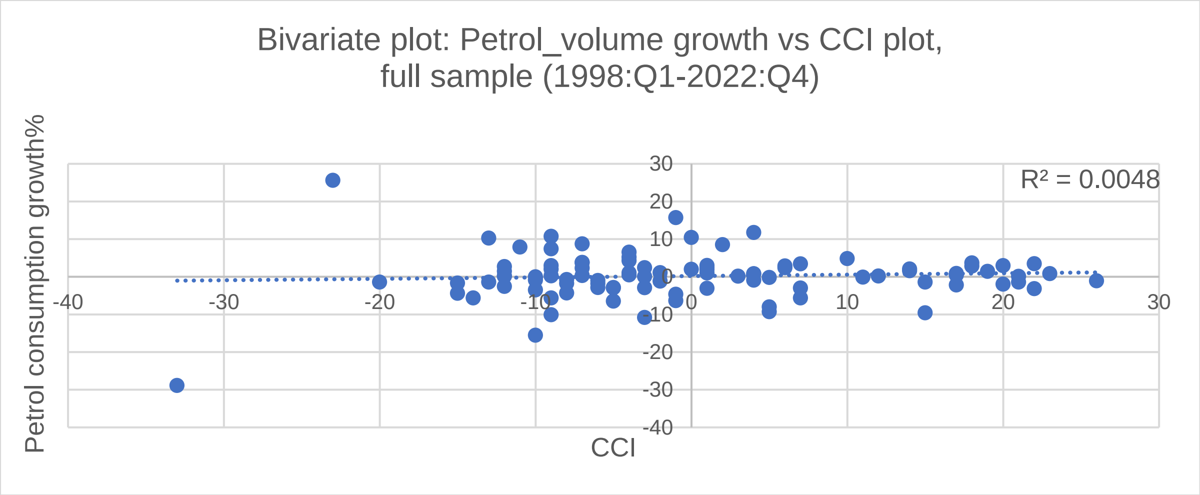

Figure 37: Bivariate plot: Petrol volume growth vs CCI, full sample (1998:Q1-2022:Q4).

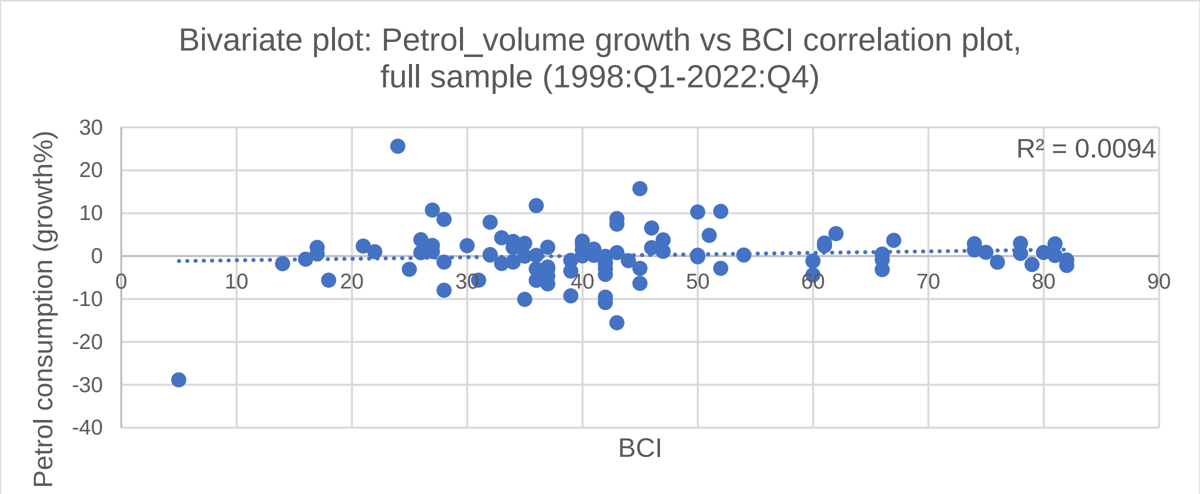

Figure 38: Bivariate plot: Petrol volume growth vs BCI correlation plot, full sample (1998:Q1-2022:Q4).

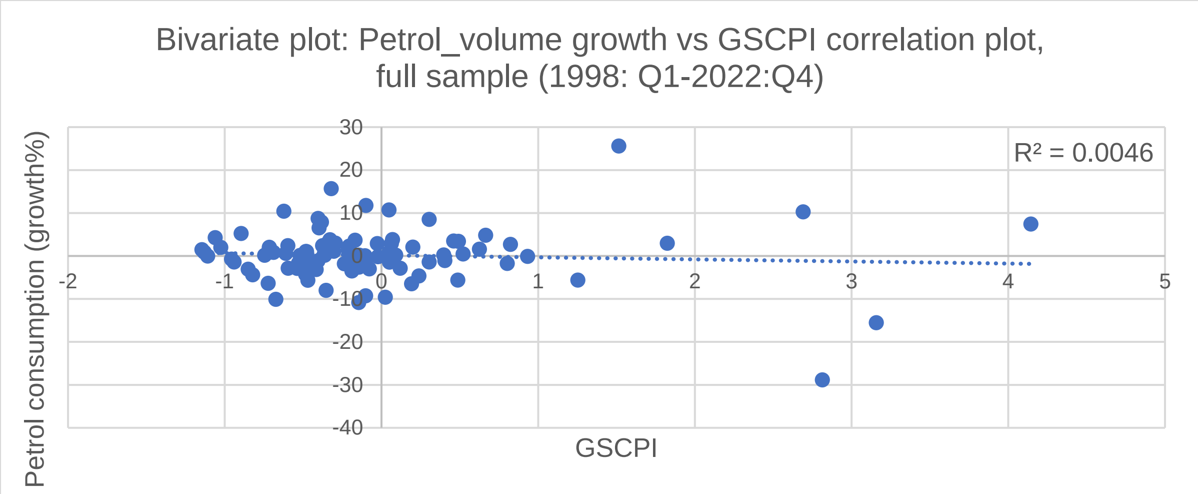

Figure 39: Bivariate plot: Petrol volume growth vs GSCPI correlation plot, full sample (1998: Q1-2022:Q4).

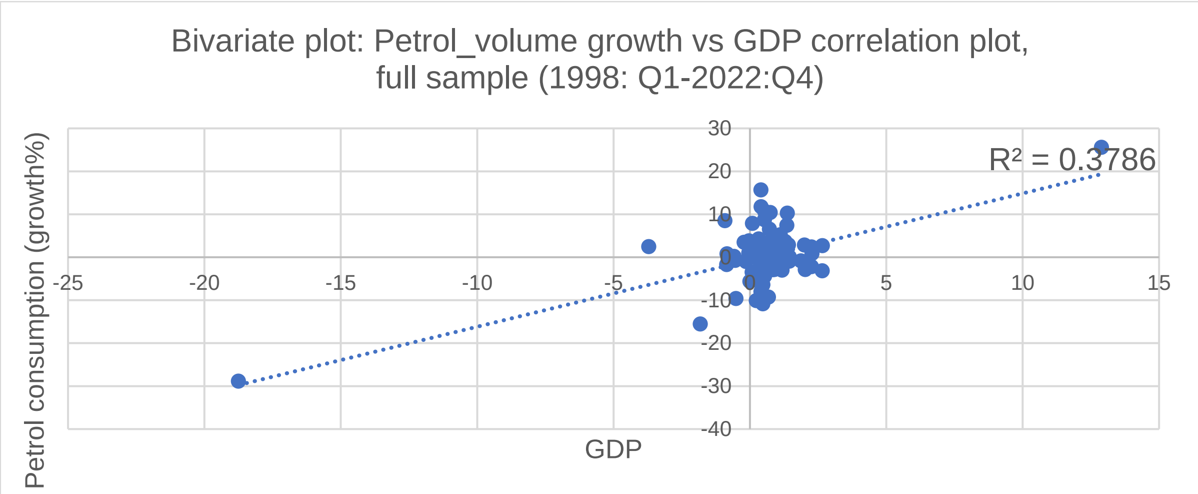

Figure 40: Bivariate plot: Petrol volume growth vs GDP correlation plot, full sample (1998: Q1-2022:Q4).

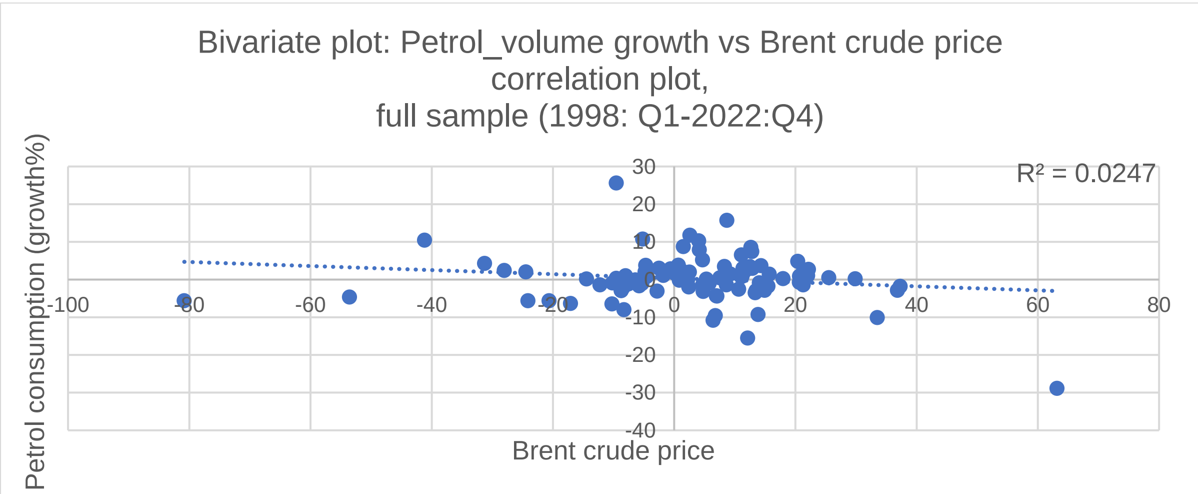

Figure 41: Bivariate plot: Petrol volume growth vs Brent crude price correlation plot, full sample (1998: Q1-2022:Q4).

The correlation analysis results indicate that there is weak relationship between petrol consumption (growth%) and CCI, as well as BCI. The relationship between petrol consumption (growth%) and GSCPI and Brent (ZAR) were found to be negative yet insignificant. A moderate positive relationship was found between petrol consumption and GDP (growth%).

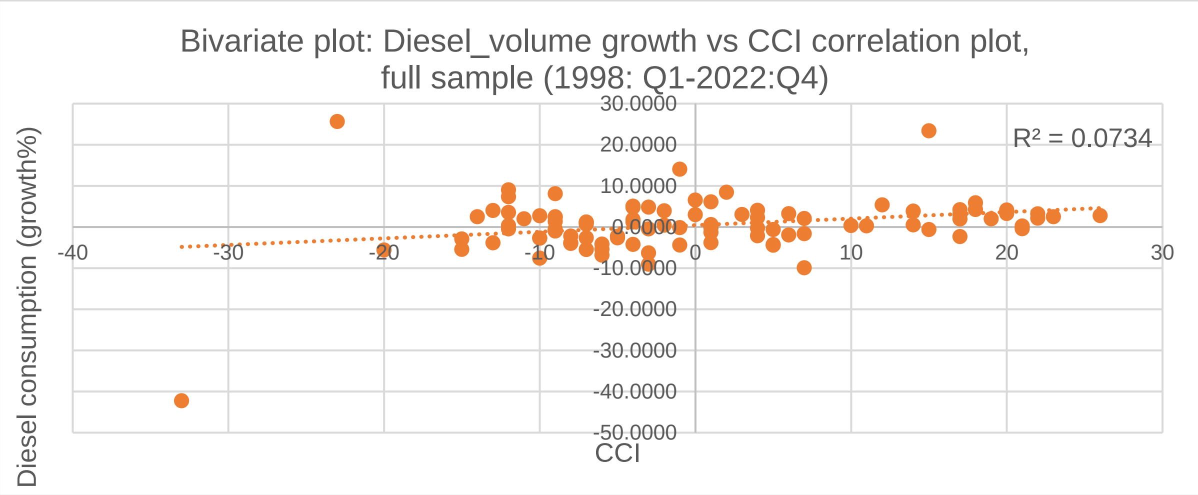

Figure 42: Bivariate plot: Diesel volume growth vs CCI correlation plot, full sample (1998: Q1-2022:Q4).

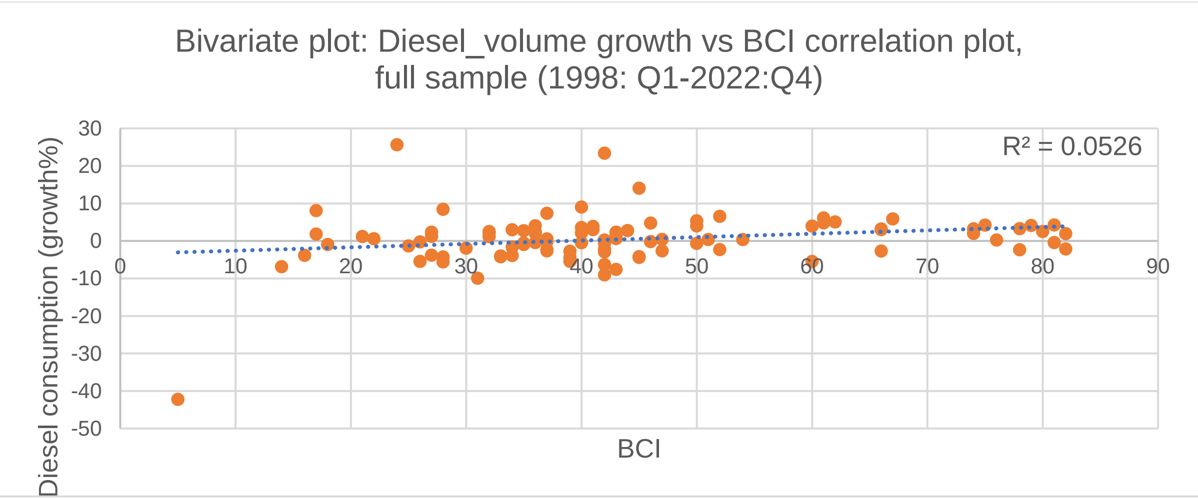

Figure 43: Bivariate plot: Diesel volume growth vs BCI correlation plot, full sample (1998: Q1-2022:Q4).

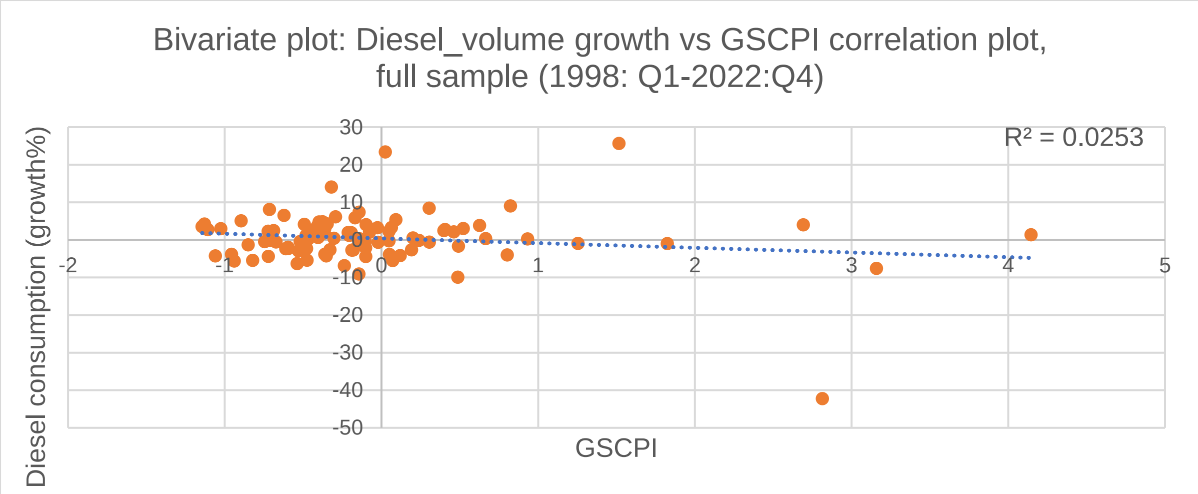

Figure 44: Bivariate plot: Diesel volume growth vs GSCPI correlation plot, full sample (1998: Q1-2022:Q4).

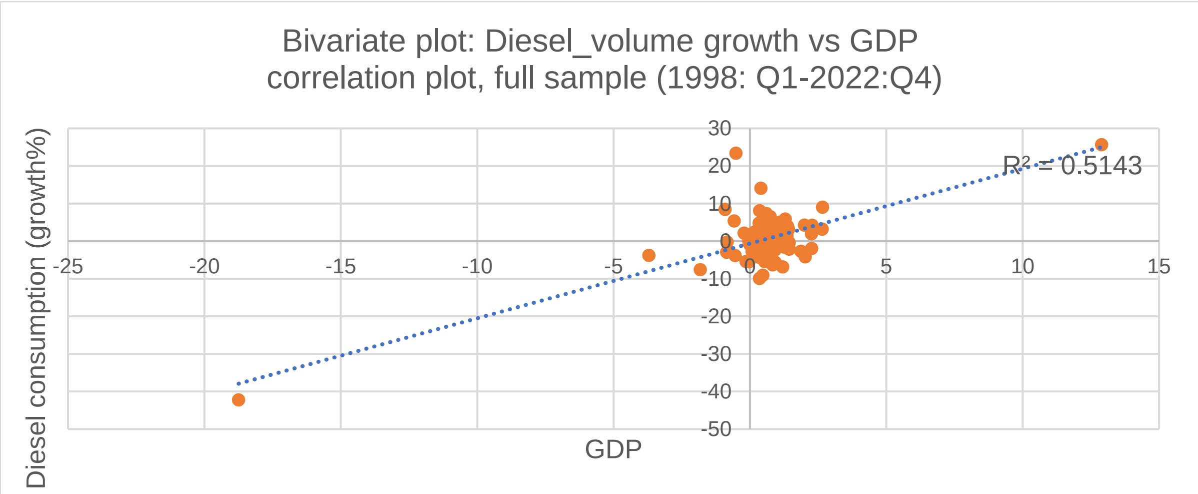

Figure 45: Bivariate plot: Diesel volume growth vs GDP correlation plot, full sample (1998: Q1-2022:Q4).

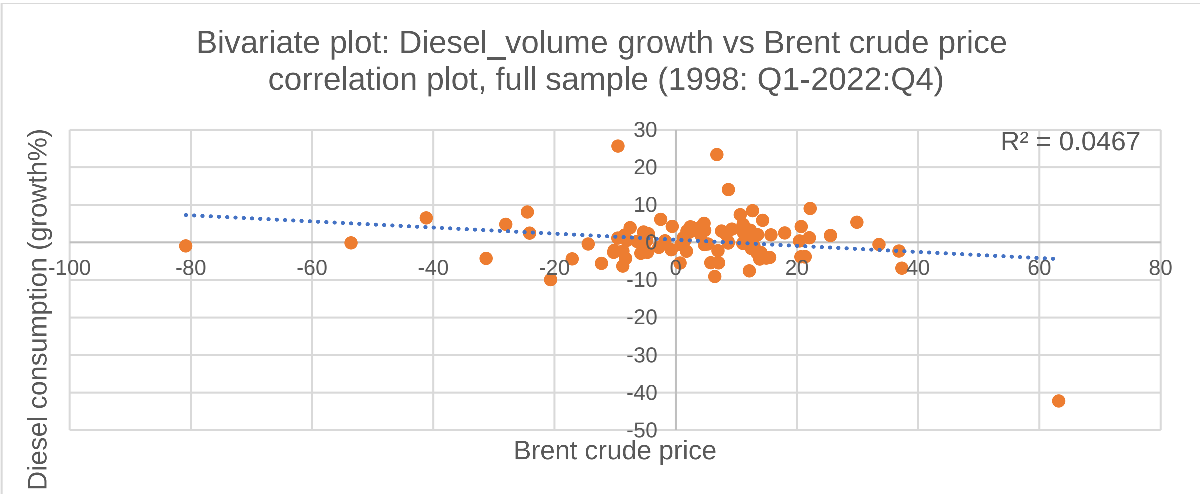

Figure 46: Bivariate plot: Diesel volume growth vs Brent crude price correlation plot, full sample (1998: Q1-2022:Q4).

With respect to diesel, the correlation plots indicate that both CCI and BCI seem to have a seemingly positive yet insignificant relationship to diesel consumption (growth%). GSCPI seems to have a negative relationship. GDP (growth%) was found to have a moderate positive relationship and Brent (ZAR) has a negative yet significant relationship to diesel (growth%).

4.5.2 Correlation Plots for the Pre-COVID-19 Period

Since across the world, the COVID-19 lockdown disruptions occurred from March 2020, in this study, the pre-COVID-19 period has been considered to be up until the last quarter of 2019 (2019:Q4).

Table 8: Pre-COVID-19 correlation.

Consumption (growth%)	Pre-COVID Sample (1998:Q1 – 2019:Q4)				
	CCI	BCI	GSCPI	GDP	Brent crude price
Petrol	0.033	0.030	0.009	-0.030	-0.028
Diesel	0.283	0.200	0.018	0.025	0.007`

Like in the preceding subsection (4.5.1), below are presented the correlation plots of petrol (Figures 48 - 52) and of diesel (Figures 53 - 57).

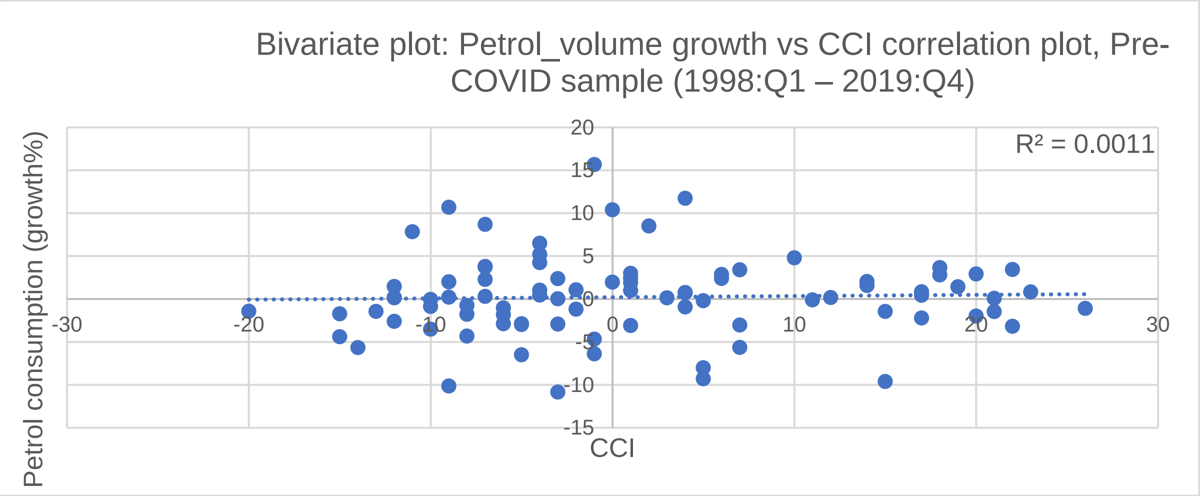

Figure 47: Bivariate plot: Petrol volume growth vs CCI correlation plot, Pre-COVID sample (1998:Q1 – 2019:Q4).

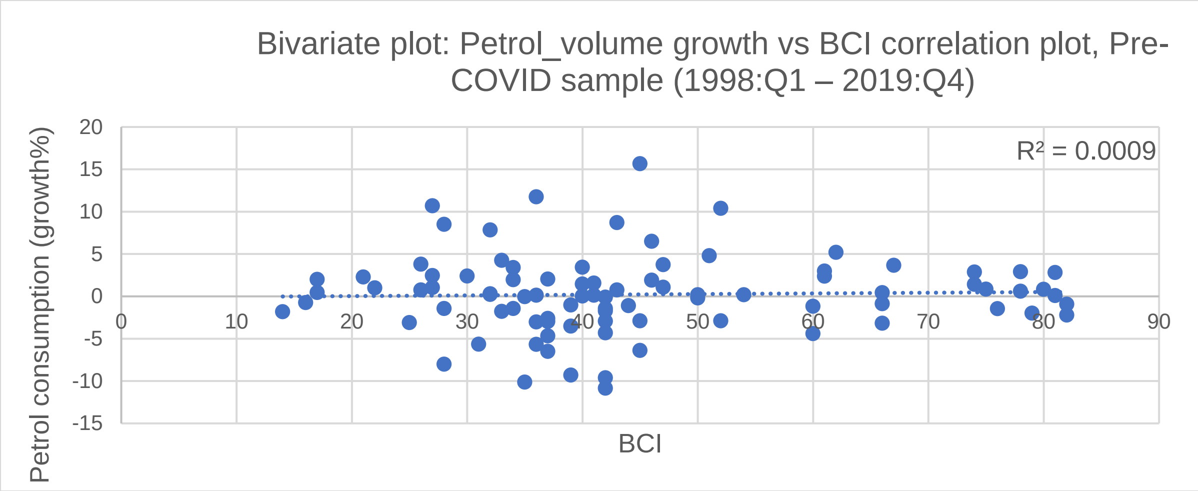

Figure 48: Bivariate plot: Petrol volume growth vs BCI correlation plot, Pre-COVID sample (1998:Q1 – 2019:Q4).

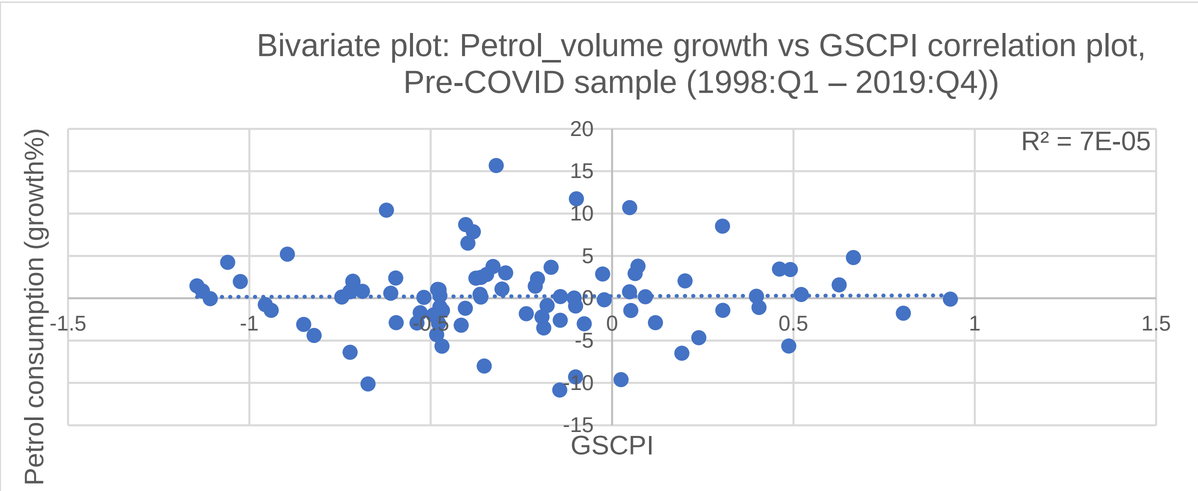

Figure 49: Bivariate plot: Petrol volume growth vs GSCPI correlation plot, Pre-COVID sample (1998: Q1-2019:Q4).

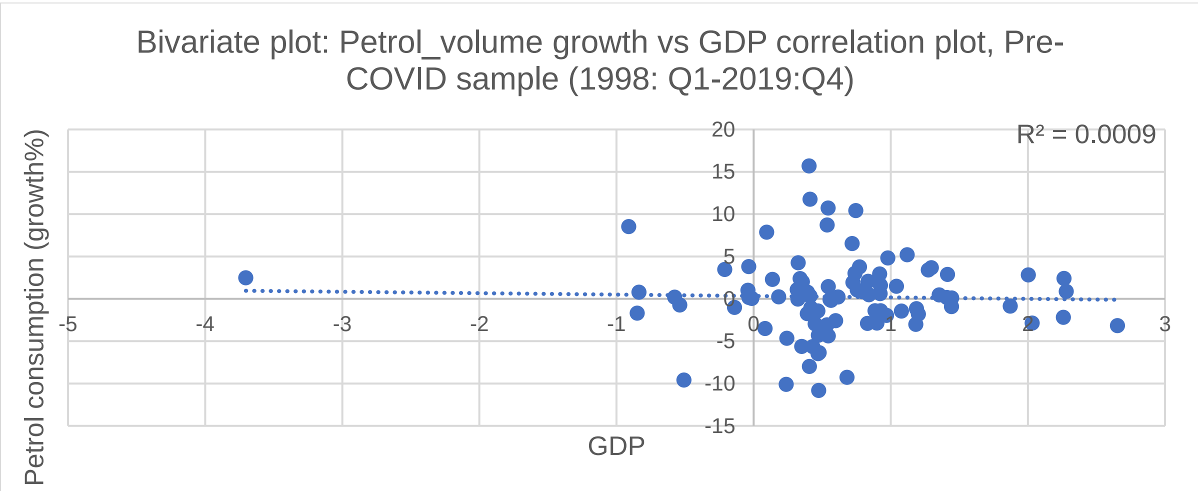

Figure 50: Bivariate plot: Petrol volume growth vs GDP correlation plot, Pre-COVID sample (1998: Q1-2019:Q4).

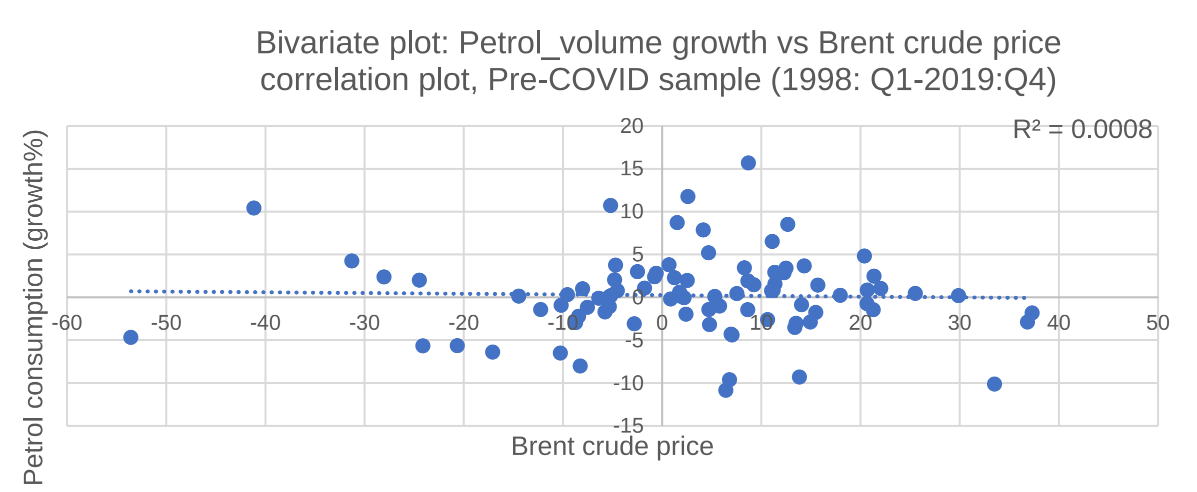

Figure 51: Bivariate plot: Petrol volume growth vs Brent crude price correlation plot, Pre-COVID sample (1998: Q1-2019:Q4).

The pre-COVID sample indicates a positive yet insignificant relationship between petrol consumption (growth%) and CCI, BCI, as well as, GSCPI. GDP (growth%) and Brent (ZAR) were found to have a negative yet insignificant relation to petrol consumption (growth%).

Next, bivariate plots for diesel consumption (growth%) against the other study variables are depicted. The pre-COVID sample is considered in this instance.

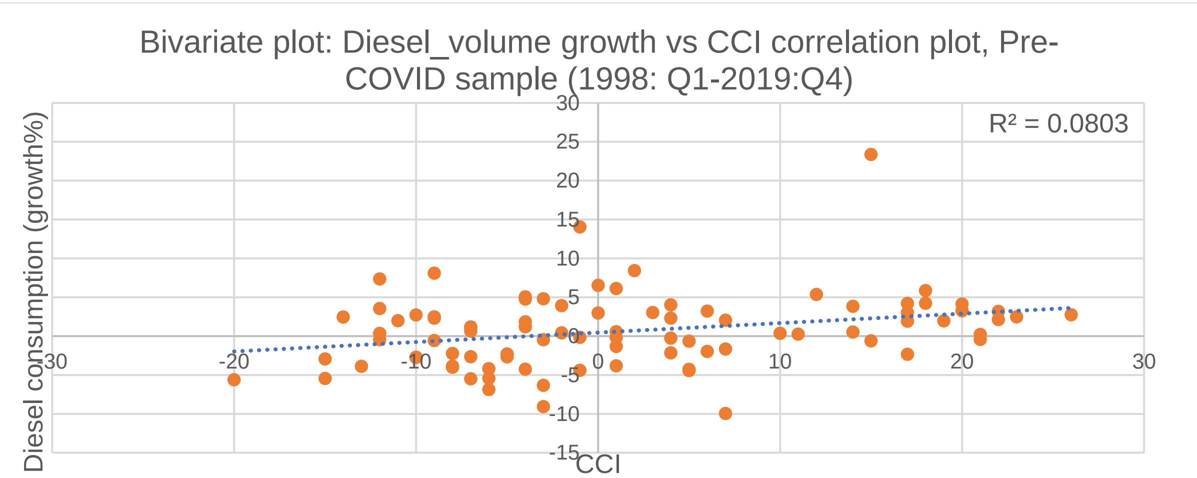

Figure 52: Bivariate plot: Diesel volume growth vs CCI correlation plot, Pre-COVID sample (1998: Q1-2019:Q4).

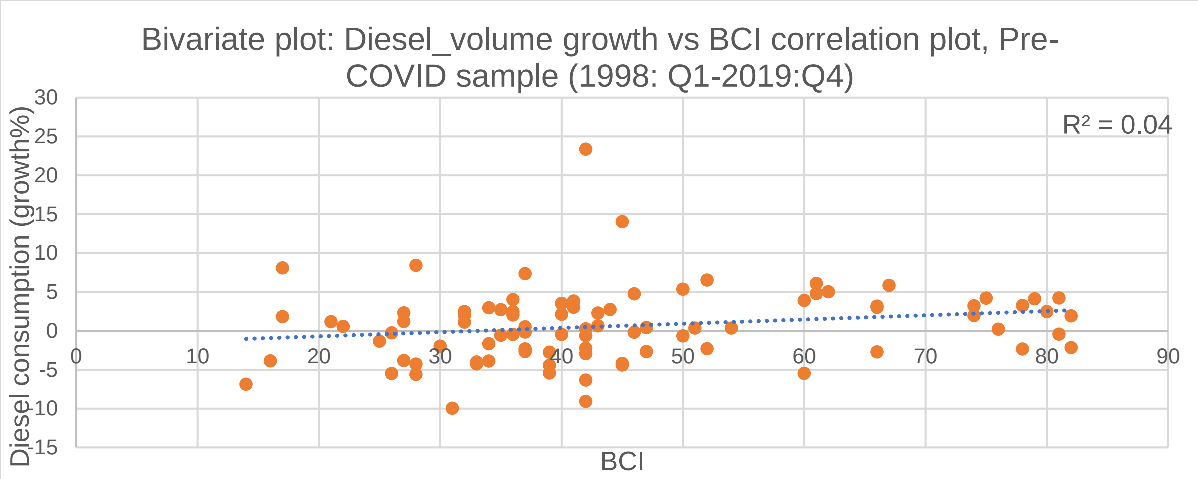

Figure 53: Bivariate plot: Diesel volume growth vs BCI correlation plot, Pre-COVID sample (1998: Q1-2019:Q4).

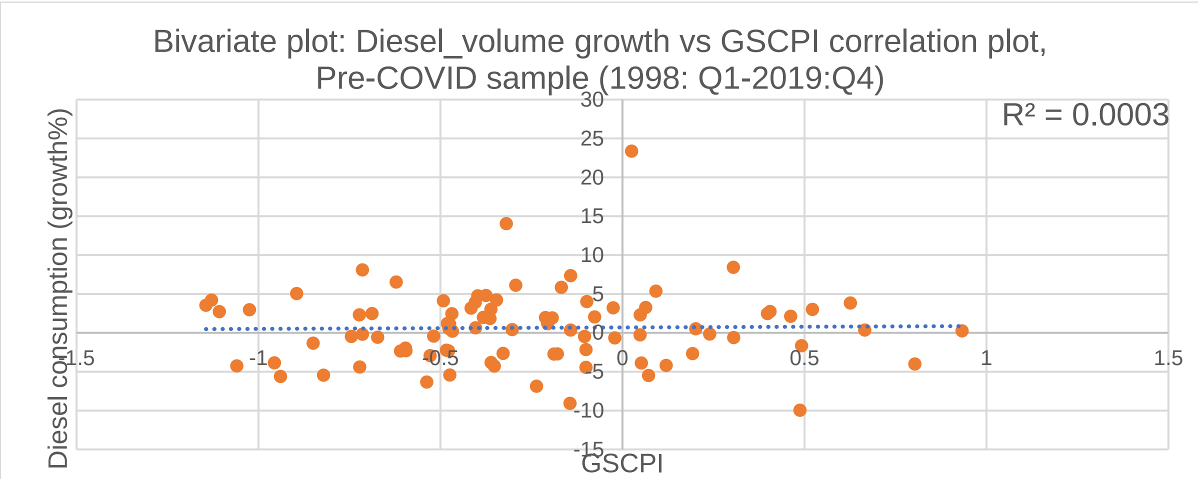

Figure 54: Bivariate plot: Diesel volume growth vs GSCPI correlation plot, Pre-COVID sample (1998: Q1-2019:Q4).

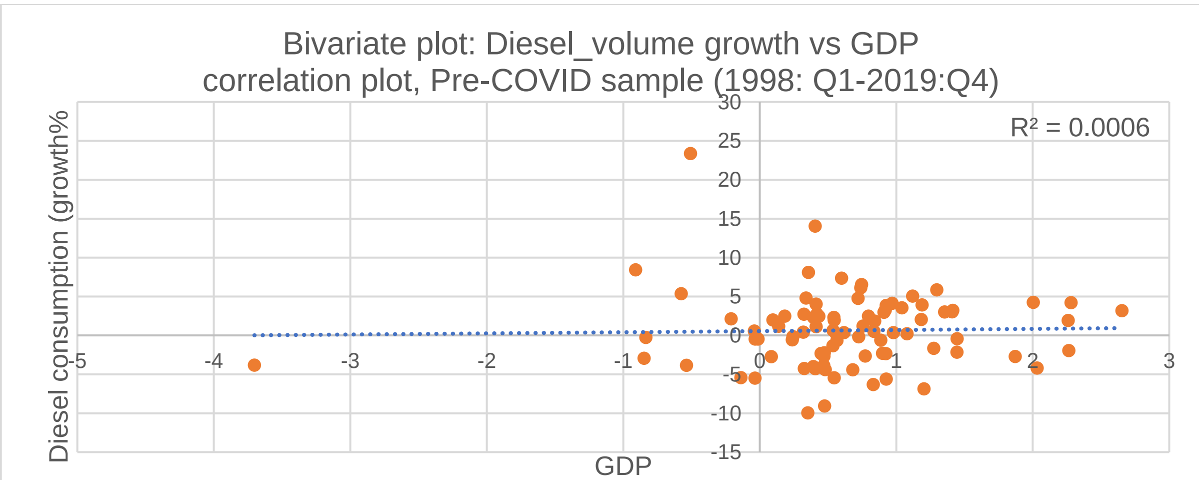

Figure 55: Bivariate plot: Diesel volume growth vs GDP correlation plot, Pre-COVID sample (1998: Q1-2022:Q4).

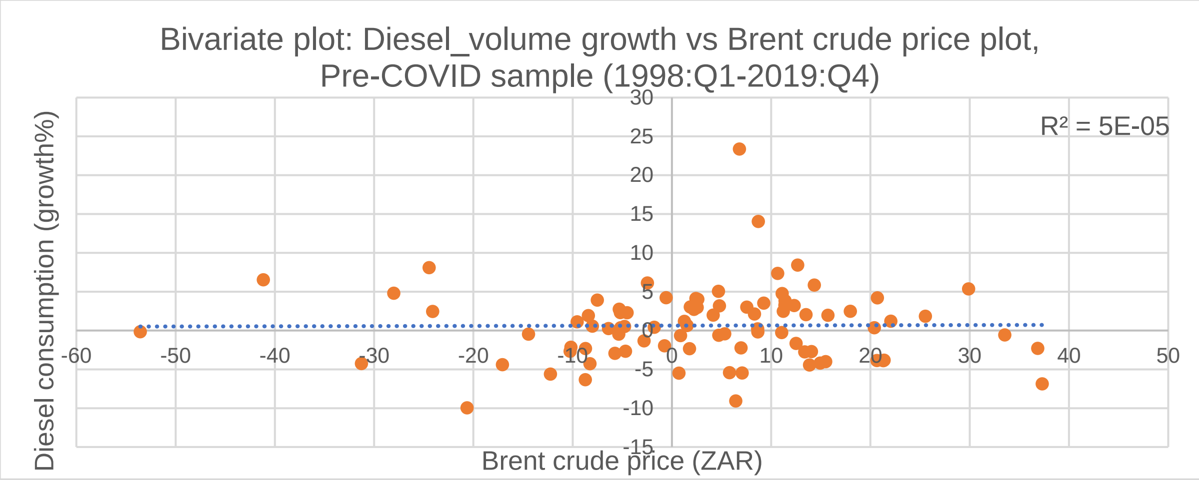

Figure 56: Bivariate plot: Diesel volume growth vs Brent crude price plot, Pre-COVID sample (1998:Q1-2019:Q4).

The correlation analysis results indicate a positive yet insignificant between diesel consumption (growth%) and all the other variables.

4.6 Results

In this exercise, the goal was first to ascertain the effect of the CCI and BCI on petrol and diesel consumption. Thereafter, the aim is to ascertain by how much is the prediction of these specific two types of petroleum product consumption improved with the addition of the GSCPI, and the price of Brent and the South African GDP predictors. The correlation of all the variables under investigation in this prediction exercise is presented below.

Table 9: Correlation of variables.

Correlation t-Statistic	DIESEL	PETROL	BCI	CCI	GDP	GSCPI	BRENT CRUDE (ZAR)
DIESEL	1.000 -----						
PETROL	0.666 8.647	1.000 -----					
BCI	0.229 2.285	0.097 0.945	1.000 -----				
CCI	0.271 2.729	0.069 0.671	0.590 7.082	1.000 -----			
GDP	0.717 9.977	0.615 7.567	0.270 2.717	0.201 1.992	1.000 -----		
GSCPI	-0.159 -1.562	-0.067 -0.656	-0.159 -1.566	-0.174 -1.713	-0.189 -1.861	1.000 -----	
BRENT CRUDE (ZAR)	-0.216 -2.146	-0.157 -1.544	0.010 0.092	0.004 0.037	-0.281 -2.844	0.141 1.382	1.000 -----

In the following sections, the prediction of petrol and diesel consumption (growth%) are performed using the full sample, and then restricting to just the pre-COVID-19 period data. We remind the reader that both the petrol and diesel consumption series being predicted are for the corresponding growth (in %) that was based on the seasonally adjusted series, which was further de-trended. The results of the prediction model also include a constant (intercept), which is denoted by “C”.

4.6.1 Predicting Petrol Consumption (Full Sample: 1998:Q1 – 2021:Q4)

First, a simple linear model to predict petrol only in terms of the CCI is evaluated, and, presented below:

Table 10: Prediction of petrol consumption (growth%) in terms of the CCI (full sample: 1998:Q1 – 2021:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	0.191 (0.400)	0.479 (0.633)
CCI	0.037 (0.056)	0.663 (0.509)

From Table 10, the CCI is insignificant (p-value 0.5088), and hence on its own CCI is not a significant predictor of the % growth in petrol consumption. Next the GDP, Brent (ZAR), and the GSCPI are added to the above regression model along with CCI, and obtain the following results:

Table 11: Prediction of petrol consumption (growth%) in terms of CCI and all the variables (full sample: 1998:Q1 – 2021:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	-0.69 (0.372)	-1.856 (0.067)
CCI	-0.028 (0.027)	-1.026 (0.308)
GSCPI	0.296 (0.424)	0.698 (0.487)
GDP	1.61 (0.182)	8.84 0
BRENT (ZAR)	0.006 (0.026)	0.218 (0.828)

Based on Table 11, the GDP is overwhelmingly explaining petrol consumption (growth%) (p-value < 0.05), and CCI along with the other two variables remains insignificant. Next, the focus is shifted on the BCI to predict petrol consumption (growth%) we observe the following:

Table 12: Prediction of petrol consumption (growth%) in terms of the BCI (full sample: 1998:Q1 – 2021:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	-1.324 (1.508)	-0.878 (0.382)
BCI	0.035 (0.03)	1.158 (0.25)

Similar to the CCI, from Table 12 there is no significant contribution of BCI for predicting petrol consumption (growth%). When the set of other predictors are added to the BCI in the above prediction model, the following is observed:

Table 13: Prediction of petrol consumption (growth%) in terms of BCI and all variables (full sample: 1998:Q1 – 2021:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	0.412 (0.756)	0.545 (0.587)
BCI	-0.026 (0.015)	-1.732 (0.087)
GSCPI	0.289 (0.426)	0.679 (0.499)
GDP	1.634 (0.169)	9.645 0
BRENT (ZAR)	0.007 (0.028)	0.246 (0.806)

Similar to CCI, in the model with the BCI it is observed that GDP remains the only significant (at 0% level) predictor of petrol consumption (growth%).
Overall, for the full sample that includes the COVID-19 period data, neither CCI nor BCI prove to be significant predictors for petrol consumption (growth%), and moreover, the dominant predictor remained GDP.

4.6.2 Predicting Diesel Consumption (Full Sample: 1998:Q1 – 2021:Q4)

The simple linear model to predict diesel in terms of CCI resulted in the following regression:

Table 14: Prediction of diesel consumption (growth%) in terms of the CCI (full sample: 1998:Q1 – 2021:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	0.443 (0.496)	0.893 (0.374)
CCI	0.16 (0.074)	2.156 (0.034)

The CCI is significant (p-value 0.034), therefore is a significant predictor of the % growth in diesel consumption based on the full-sample. The GDP, Brent (ZAR), and the GSCPI is then added to the above regression model along with CCI, and obtain the following results:

From Table 15, it is observed that while GDP is significantly correlated to diesel consumption ($p<0.05$), CCI continues to be a significant predictor of diesel consumption ($p=0.042$). Brent (ZAR) and GSCPI were found not to be significant predictors of diesel.

Table 15: Prediction of diesel consumption (growth%) in terms of CCI and all the variables (full sample: 1998:Q1 – 2021:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	-0.566 (0.386)	-1.468 (0.146)
CCI	0.079 (0.038)	2.066 (0.042)
GSCPI	-0.03 (0.265)	-0.112 (0.911)
GDP	1.895 (0.229)	8.274 0
BRENT (ZAR)	-0.009 (0.025)	-0.366 (0.715)

Next, the focus on using BCI to predict petrol consumption (growth%) and the following is observed:

Table 16: Prediction of diesel consumption (growth%) in terms of the BCI (full sample: 1998:Q1 – 2021:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	-3.492 (2.181)	-1.601 (0.113)
BCI	0.09 (0.044)	2.044 (0.044)

The BCI is significant (p-value = 0.043), implying that BCI is a significant predictor of the % growth in diesel consumption. Next, the GDP, Brent (ZAR), and the GSCPI are added to the above regression model along with BCI, and obtain the following results:

Table 17: Prediction of diesel consumption (growth%) in terms of BCI and all the variables (full sample: 1998:Q1 – 2021:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	-1.25 (0.665)	-1.881 (0.063)
BCI	0.015 (0.015)	1.002 (0.319)
GSCPI	-0.148 (0.199)	-0.747 (0.457)
GDP	1.938 (0.204)	9.509 0
BRENT (ZAR)	-0.006 (0.025)	-0.264 (0.792)

International indicators BRENT (ZAR) and GSCPI were found to have an insignificant impact on the predictability of diesel consumption. While GDP was found to have a significant impact on diesel (growth%) predictability, BCI was found to fall out of significance (p-value =0.319) when combined with the other variables.

The overall findings of the above exercise suggest that GDP is the predominant predictive indicator for diesel (growth%) predictability. Interestingly, on its own BCI is a significant predictor, however, in the model that includes GDP, it becomes insignificant as also Brent (ZAR), and the GSCPI.

4.6.3 Predicting Petrol Consumption (Pre-COVID-19 sample 1998:Q1 – 2019:Q4)

The data series is then restricted to pre-COVID-19 period, that is only use the period 1998:Q1 to 2019:Q4, and evaluate the model prediction model using CCI and BCI separately, we observe the following respectively:

Table 18: Prediction of petrol consumption (growth%) in terms of CCI (Pre-COVID-19 sample 1998:Q1 – 2019:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	0.014 (0.026)	0.536 (0.594)
CCI	0.208 (0.315)	0.661 (0.51)

Table 19: Prediction of petrol consumption (growth%) in terms of BCI (Pre-COVID-19 sample 1998:Q1 – 2019:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	0.008 (0.011)	0.717 (0.476)
BCI	-0.129 (0.646)	-0.199 (0.842)

Neither CCI nor BCI on their own prove to be significant predictor for petrol consumption (growth%) with p-values at 0.594 and 0.476 respectively. The remaining three predictor variables of GDP, Brent (ZAR) and GSCPI are added to the CCI and BCI separately, we observe the following respectively:

For predicting petrol consumption (growth%), it seems that both in the full sample as well as the restricted sample preceding COVID-19, neither CCI nor BCI prove to be significant predictors. Further, only none of the other predictors emerge as significant for predicting petrol consumption (growth%) in the restricted data model.

Table 20: Prediction of petrol consumption (growth%) in terms of CCI and all the variables (Pre-COVID-19 sample 1998:Q1 – 2019:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	0.021 (0.032)	0.664 (0.509)
CCI	-0.246 (0.445)	-0.553 (0.582)
GSCPI	0.362 (0.467)	0.774 (0.441)
GDP	-0.01 0.028	-0.346 (0.731)
BRENT (ZAR)	-0.06 (0.71	-0.085 (0.933)

Table 21: Prediction of petrol consumption (growth%) in terms BCI and of all the variables (Pre-COVID-19 sample 1998:Q1 – 2019:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	-0.219 (0.669)	-0.328 (0.744)
BCI	0.016 (0.015)	1.05 (0.297)
GSCPI	0.107 (0.701)	0.152 (0.879)
GDP	-0.325 (0.489)	-0.665 (0.508)
BRENT (ZAR)	-0.009 (0.028)	-0.325 (0.746)

4.6.4 Predicting Diesel Consumption (Pre-COVID-19 sample 1998:Q1 – 2019:Q4)

Finally, the prediction models are evaluated for diesel consumption for the pre-COVID-19 period, first in terms of CCI and BCI separately, as follows:

Table 22: Prediction of diesel consumption (growth%) in terms of CCI (Pre-COVID-19 sample 1998:Q1 – 2019:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	0.461 (0.365)	1.263 (0.21)
CCI	0.122 (0.032)	3.755 0

Table 23: Prediction of diesel consumption (growth%) in terms of BCI (Pre-COVID-19 sample 1998:Q1 – 2019:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	-1.792 (0.799)	-2.242 (0.028)
BCI	0.054 (0.014)	3.815 0

It is observed that in the simple linear setting, both CCI and BCI prove to be significantly (p-value < 0.05) explaining diesel consumption (% growth) in the pre-COVID19 period. Next, the other variables of interest are added to both the above models, and observe the following:

Table 24: Prediction of diesel consumption (growth%) in terms of CCI and all the variables (Pre-COVID-19 sample 1998:Q1 – 2019:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	0.468 (0.735)	0.636 (0.526)
CCI	0.142 (0.045)	3.155 (0.002)
GSCPI	-0.877 (0.795)	-1.102 (0.274)
GDP	-0.411 (0.853)	-0.482 (0.631)
BRENT (ZAR)	-0.006 (0.032)	-0.171 (0.865)

Table 25: Prediction of diesel consumption (growth%) in terms of BCI and all the variables (Pre-COVID-19 sample 1998:Q1 – 2019:Q4).

Variable	Coefficient (Std. Error)	t-Statistic (p-value)
C	-1.964 (0.873)	-2.25 (0.027)
BCI	0.067 (0.023)	2.958 (0.004)
GSCPI	0.232 (0.712)	0.326 (0.745)
GDP	-0.541 (0.837)	-0.646 (0.52)
BRENT (ZAR)	0 (0.031)	0.011 (0.991)

CCI and BCI are significant predictors (p-value < 0.05) for diesel consumption (% growth) in the pre-COVID-19 period. What is even more interesting is that in both the above models for the pre-COVID-19 period, GDP does not prove to be a significant predictor for diesel consumption (% growth), as also Brent (ZAR) and the GSCPI.

4.7 Discussion of Results and Concluding Remarks

The objective of this exercise was to investigate the degree to which consumer and business sentiments drive the predictability of South Africa's petrol and diesel consumption (growth%). This insight can be leveraged by petrochemical companies to understand their customer demand profiles and enable strategic supply chain planning. The final domestic predictor variables used in this exercise include the GDP and Brent crude price (ZAR), and the international predictor variable, GSCPI, was also considered in the exercise.

Table 26: Summary of the significant predictor variables for both diesel and petrol consumption (growth%) from the simple linear regression (SLR) model using CCI and BCI separately, and the multiple linear regression (MLR) models with each of CCI and BCI with the other 3 predictors.

		Model type	
Period		SLR	MLR
Pre-COVID-19	Diesel	CCI, BCI	CCI and BCI
	Petrol		
Full sample	Diesel	CCI, BCI	CCI and GDP
	Petrol		GDP

From Table 26 the following is observed: In the pre-COVID-19 period for diesel consumption (growth%) prediction, both CCI and BCI emerge as significant explanatory predictors from the simple linear regression model. In the multiple linear regression model, for the same period, both CCI and BCI continue to remain significant, while the other predictor variables are not significant.

Again, from Table 19, for the full sample period, as in the pre-COVID-19 period, both CCI and BCI emerge as significant predictors in the simple linear regression models. In the MLR for prediction of diesel, however, only CCI and GDP emerge as significant predictors separately, while in the MLR with BCI, none of the predictor variables emerge as significant. For petrol, neither CCI nor BCI emerge as significant in neither of the SLR and MLR models, with only GDP being the significant predictor.

The above summary reflects the fact that commercial industries are the main consumers of diesel, and that the BER's BCI reflects the sentiments of manufacturers, contractors, retailers, wholesalers and new vehicle dealers. This thesis asserts that the difference observed between the BCI's individual predictive contribution in the full sample versus in the pre-COVID-19 periods may be attributed to the difference in these industry's inability to recover to the pre-pandemic levels (Stats SA, 2022). Based on the results, it is suggested that perhaps the BER's CCI might not necessarily capture the sentiments of individual petrol and diesel retail customers, and may be reflective of the fact that over 67,35% of South Africans living in urban areas to pursue work opportunities (Statista, 2022), at least a third of this population uses public transport, such as taxis (33.6%), less than one third uses private vehicles (29.8%) and the remining use either bus or train to commute (Statistics SA, 2022).

Overall, GDP is a key driver to the prediction of petrol and diesel consumption (growth%) based on the MLR results from the full sample. Although indirect influencers of GDP (Brent crude price and GSCPI) were found not to be significant drivers for predicting petrol and diesel consumption (growth%), they give context to the behaviour of the GDP (% growth) used in the prediction model. The pre-COVID-19 period predictive models indicates that prior to the pandemic, GDP did not emerge as a significant predictor for both petrol and diesel consumption, and may be there exists some non-linear relationship, which was not considered within the scope of this exercise.

The full sample prediction model captured the significance of the supply chain shock that resulted in a contracting economy that impacted household income and even restricted travel as a result of the pandemic. Inversely, the pre-COVID-19 period was subject to a stable GDP growth that saw a steady increase in petrol and diesel consumption leading up to the pandemic. Interestingly, none of the macro-economic variables were found to be significant predictors in both full sample and pre-COVID-19 predictive models.

The prediction model results for the full-sample and pre-COVID periods demonstrate the impact that the pandemic has had on supply chain dynamics. To improve the predictability of petrol and diesel consumption (growth%), it is recommended that petrochemical companies invest in the understanding their customer profiles and use this information in combination with significant drivers as indicated by the prediction model results. On a strategic level, such insight can assist in ensuring that refineries meet the national petroleum demand and on a tactical level, this information can be used to plan and optimise petroleum deliveries across the distribution network.

5. CONCLUSIONS AND IMPLICATIONS

5.1 Introduction

The aim of this study was to address the overarching research question of:

What are the capabilities that are necessary to perform supply chain analytics using customer data?

To that end, Chapter 1 of the thesis highlighted the evolution of the SCM concept in response to technological innovations, as well as, the associated challenges of the emerging supply chain landscape. A literature review was conducted, which indicated that the resulting DSC is driven by the integration of physical and technological systems which have resulted in increased dynamic customer demands and vulnerabilities to external supply chain disruptions. The emerging supply chain landscape is described in the context of a cyber-physical system (CPS) and consists of the alignment of business processes and information systems as potential enablers to improved supply chain decision-making and improved network performance.

As a result of the digitalisation of supply chain networks, both small data and big data flows in and out of supply chain processes. The analysis of this data provides insight to the state of the supply chain and can be analysed using techniques such as SCA – descriptive, predictive and prescriptive analytics. The analytics models use historical data to reconstruct disruption scenarios and real-time data to anticipate emerging disruptions. It is however noted that there exists a gap between the use of analytics tools and the ability of the users to extract information from them as per strategic business needs.

The integration of cyber-physical systems has also resulted in an interconnected global supply chain that is vulnerable to supply chain disruptions. These disruptions are classified as environmental, geopolitical, economic, and technological.

The Supply Chain Operations Reference (SCOR) model is as a traditional SCM that can be adapted to guide benchmarking and improvement of novel supply chain operations. The model's *Plan, Source, Make, Deliver* and *Return* are key business process activities for meeting customer demand. The theory reviewed in the chapter highlighted how the model has evolved in response to supply chain technological innovations and although shortfalls of the model are noted, it is proposed that practitioners continue to use as a foundation for supply chain analysis and improvement. This view does not dismiss the need for a novel approach to managing the emerging customer-driven supply chain.

The management of logistics that ensures the movement of goods through the supply chain network and therefore identify the crude oil supply chain supply chain landscape as central to the flow of goods and services across the supply chain and the consumption of oil provides a measure for assessing global supply chain health. A South African petrochemicals company is therefore used as a case study in Chapter 3 to propose a set of capabilities for linking customer demand to supply chain processes. And finally, the use of SCA is demonstrated in Chapter 4, where secondary data is used to develop predictive models for petrol and diesel consumptions (growth%).

5.2 Conclusions about Research Issues or Hypotheses

This thesis asserts that there is a need for the development of SCA capabilities using customer data for improved supply chain management. The literature discussed in the thesis highlights that technology has altered the landscape of traditional supply chains into that of being customer and data driven. The following sub-sections recapitulates the highlights of the thesis.

5.2.1 Linking customer data to the supply chain

The view adopted in this thesis is by Biswas and Sen (2016) who suggested that in a data-driven supply chain structure, demand is initiated by customer needs, and flows through successive stages to the supplier. Although much has been invested in supply chain technologies by organisations, the capabilities that are required to translate the data generated by these technologies is still lacking, which has resulted in a missing link for the integration of process. The focus is on the most critical data that flows through supply chains, that is, customer demand.

It is proposed the integration of CRM and SCA Capabilities through a set of hypotheses which were tested by means of a Structural Equation Model (SEM). A petrochemicals company was used as a case study and a web-based survey was administered to key stakeholders of the company's supply chain processes. A set research questions were developed to test a set of hypotheses relating to People, Process and Technology Capabilities were developed.

The data collected through the survey was initially interrogated using correlation analysis. Results of the correlation analysis indicated a positive correlation between the implementation of business intelligence tools to the embedding SCA. This finding is supported by literature, where scholars have discussed the perceived value by organisations that is associated with the implementation of technology and data harvesting. The establishment of customer centric processes was also found to be positively correlated to the following: (i) the integration of information flow; (ii) the training of staff on Business Intelligence (BI) tools; and (iii) the establishment of customer-centric supply chain processes.

A customer-centric supply chain articulates the data to be harvested and shared among supply chain processes in the context of customer demand. The results further highlighted the positive association between BI tools and the enhancement of SCA capabilities. The training staff on BI tools and interpretation of this data through SCA techniques provides insight which enable the organisation to develop a cohesive view of its supply chain processes and facilitates informed decision-making.

Interestingly, the establishment of a customer-centric culture was found not to be significantly correlated with the effective implementation of a Customer-Relationship-Management strategy. This finding highlights the inability by the organisation's management to change organisational culture and evolve from making reactive, to making predictive and prescriptive supply chain decisions.

Next, Confirmatory analysis within the SEM framework was used to test the two SEM models developed. Model-1 comprised of the latent variables Technology and People capabilities and Model -2 comprised of the latent variables People, Process and Technology capabilities.

People Capabilities

$H_{1,1}$: *A customer-centric organisational culture has the potential to improve the organisation's SCA capabilities.*

$H_{1,2}$: *The effective implementation of a Customer-Relationship-Management strategy is dependent on top-management buy-in.*

The results suggest the respondents lack of awareness of the impact that a customer-centric organisational culture has on improving the organisation's SCA capabilities through People Capabilities. This reiterates the missing link between customer data and supply chains. The inability of an organisation to create a customer demand-driven environment inhibits the ability to source relevant customer data and meet customer demand using insights extracted from this data. The implementation of CRM strategies needs to expand beyond the implementation systems that merely collect customer information to the strategic integration of data into supply chain processes. Parallel to this, top-management needs to drive the change management that is needed for organisational readiness.

Process Capabilities

$H_{2,1}$: *It necessary to establish customer-centric supply chain processes in order to improve SCA capabilities.*

$H_{2,2}$: *The integration of information flow between the supply chain processes (planning, sourcing, making/raw material transformation, delivery, return and enabling processes) improves SCA capabilities.*

From Model-2 CFA output it is observed that with the introduction of the Process latent variable, the loading of Technology on its measurement variables, and on Process is significant. However, the loading of People on its measurement variables as well on Process latent variable remains insignificant. This result supports that there is a positive correlation between the training of staff on Business Intelligence (BI) tools and the establishment of customer-centric supply chain processes.

Technology Capabilities

$H_{3,1}$: *Organisation's investment in Business-Intelligence tools (such as Power BI, QlikView, SAP associated platforms, etc.), improves SCA capabilities within a function/business unit*.

$H_{3,2}$: *Training of staff on Business-Intelligence tools (such as Power BI, QlikView, SAP associated platforms, etc.), improves SCA capabilities in a function/business unit.*

$H_{3,3}$: *The nature of the petrochemicals industry hinders an organisation's ability to effectively implement SCA capabilities.*

The CFA output for Model-1 indicated that the Technology latent variable has significant loading on its measurement variables, while none of the loading from the People latent variable are significant. This finding further highlights the perceived value of BI tools in supply chain optimisation. Model-2 indicates the loading of Technology on its measurement variables and on Process to be significant.

The survey results affirm that there is indeed a missing link between customer data and supply chains. The strategic implementation of CRM needs to form an integral component of the operating model in order to establish a customer centric culture and establish customer-centric processes that enable the integration of customer demand to supply chain processes.

Next, the enhancement of SCA capabilities using a quantitative approach were considered. Chapter 4 of the thesis developed and tested predictive models for South Africa's consumption of petrol and diesel (growth%).

5.2.2 Predicting South Africa's Petroleum Consumption

A review of the crude oil supply chain was conducted where Brent crude was adopted as the official oil benchmark for the exercise. It is noted that the significance of Brent crude price on economic activities of both crude oil producing and importing countries. A negative link is established between high Brent crude oil prices and economic activities.

Historical data was collected which included: South Africa's petrol and diesel sales volumes (in million litres), CCI, BCI, GDP, GSCPI and Brent crude price (ZAR). The data sourced was seasonally adjusted using the United States Census Bureau's X-13ARIMA-SEATS seasonal adjustment method, and subsequently detrended.

The prediction regression exercise involved predicting both petrol and diesel consumption (growth%) separately using the full-sample and then excluded the COVID-19 period, that is including data until 2019:Q4.

The following hypothesis of interest were developed for both petrol and diesel consumption, individually:

i H1: CCI has a positive effect on petrol/diesel consumption

The full sample prediction model indicated that, on its own, CCI is not a significant petrol consumption (growth%). The introduction of GDP, Brent (ZAR), and the GSCPI to the prediction did not prove to improve the prediction of CCI in the prediction model. However, on its own, CCI was found to be a significant predictor of diesel consumption (growth%). The CCI continued to remain a significant diesel consumption (growth%) with introduction of GDP, Brent (ZAR), and the GSCPI.

The pre-COVID sample found CCI to be an insignificant predictor of petrol consumption (growth%) on it and even when combined with predictor variables GDP, Brent (ZAR), and the GSCPI. CCI continues to be a significant predictor of diesel consumption (growth%) on its own combination with the other predictor variables.

ii H2: BCI has a positive effect on petrol/diesel consumption

BCI was found to be an insignificant predictor of petrol consumption (growth%) on its own and in combination with other relevant predictors in the full sample model. Still in the full sample model, BCI is a significant predictor of the % growth in diesel consumption on its own but falls out of significance when combined with the other variables.

The pre-COVID period sample predictive model indicates BCI to be an insignificant predictor of petrol consumption (growth%), on its own and in combination with other variables. BCI continues to be a significant predictor of diesel consumption (growth%) on its own and in combination with the other variables.

iii GSCPI and Brent (ZAR) have a negative effect on petrol/diesel consumption

Interestingly, neither GSCPI and Brent (ZAR) were found to be of any significance in any of the prediction model.

iv SA GDP has a positive effect on petrol/diesel consumption

The GDP was found to be a significant predictor of petrol and diesel consumption (growth%) in the full sample models. Its significance however diminishes in the pre-COVID predictive models.

5.3 Overarching Summary

The thesis introduced the missing integrant in supply chains as the ability to translate customer data into insight that can be used for decision-making. Three aspects were considered to address the research problem. First, it was concluded that the SCOR model is a traditional framework that is relevant and can be used as a guideline for the optimisation of supply chain processes. Second, while theory supports the view of the proposed approach to link customer demand to the supply chain, the survey results reflected conflicting views. The theoretical and practical understanding of People, Process and Technology capabilities that are proposed needs to be enhanced in order to guide the integration of SCA and CRM. Finally, it was demonstrated that secondary data that captures customer and business sentiments can be used as predictive drivers for petrol and diesel consumptions, subject to disruptive supply chain events such as COVID-19. The predictive significance of GDP in the full sample also captures the significance of macro-economic data in the predictive analysis of supply chains.

In conclusion, the qualitative investigation of this study highlights that while practitioners understand the role of technology in supply chains, the significance of a customer-centric organisation and a clear CRM strategy communication from top management is yet to be understood. And lastly, focusing on petrol and diesel consumption, the quantitative investigation demonstrates that secondary data that captures both the customer and business sentiments, as well as, domestic and international predictive indicators, can be used to anticipate demand and drive decision-making.

5.4 Implication of this Research for Supply Chain Management

The novel supply chain is not only data-driven, but also customer demand driven and requires a novel approach for the optimisation thereof. This thesis views SCA as a key technique for the translation of customer data into supply chain insight. Parallel to this, the integration of strategic CRM is proposed to integrate customer demand into the supply chain. Finally, the predictive regression model presented herein highlights the significance of analytics in gaining insight to customer demand profiles. The novelty of the predictive model in this thesis is the combined use of CCI, BCI, GDP, Brent crude price (ZAR) and GSCPI to predict petrol and diesel consumption.

5.5 Implication of this Research for Policy and Practice

Organisations need to go beyond investing in technology and focus on enabling their practitioners with capabilities that are required to translate data into insight. The role of a customer-centric organisation culture should be further emphasized and embedded by top leadership within the organisation. Customer demand should be viewed and analysed in the context of an end-to-end supply chain, where each supply chain process uses customer data to analyse their processes on a descriptive, predictive and prescriptive level.

The supply chain distribution network of both petrol and diesel is vast for many of the major oil players. The customer take-on process is generally initiated by vetting customers and ensuring that customers adhere to any relevant legislation that is mandatory in order to do business with the petrochemicals company. In this context, customers include both retail and commercial petrol and diesel consumers. Once customers are accepted to do business, they are then able to place orders for products via the relevant channels established by the petrochemicals company, this includes direct contact with a Sales Representative, Customer Portal, etc. Disruptions to the distribution network usually results in longer sales lead times and the potential loss of unsatisfied customers.

Organisations should also invest in systems that capture their customer sentiments while also integrating macro and micro-economic predictors into their forecasting models. The regulatory bodies of industries should consider supporting its members in this regard. For example, a regulatory body like SAPIA should conduct surveys that capture the sentiments of the consumers of petroleum products and share this information with them on a quarterly basis. This information can then be used in combination with other predictive indicators to predict that consumption of petroleum products.

5.6 Potential for Future Scope of the Research

The integration of CRM and SCA can be further explored, and other alternative capabilities investigated. The proposed capabilities herein can also be used to administer the thesis survey (Chapter 3) in different industries, or even in other countries, to observe the difference or commonalities in results.

The full sample data considered for the exercise in Chapter 4 ranges from 1998:Q1 as this is the earliest period when GSCPI is reported. Future research may consider an alternative index that will allow for a longer range for the prediction exercise.

Alternative prediction statistical models should be explored, which include the consideration of other consumer and business indices. Future research should consider performing a similar analysis for other crude oil importing countries.

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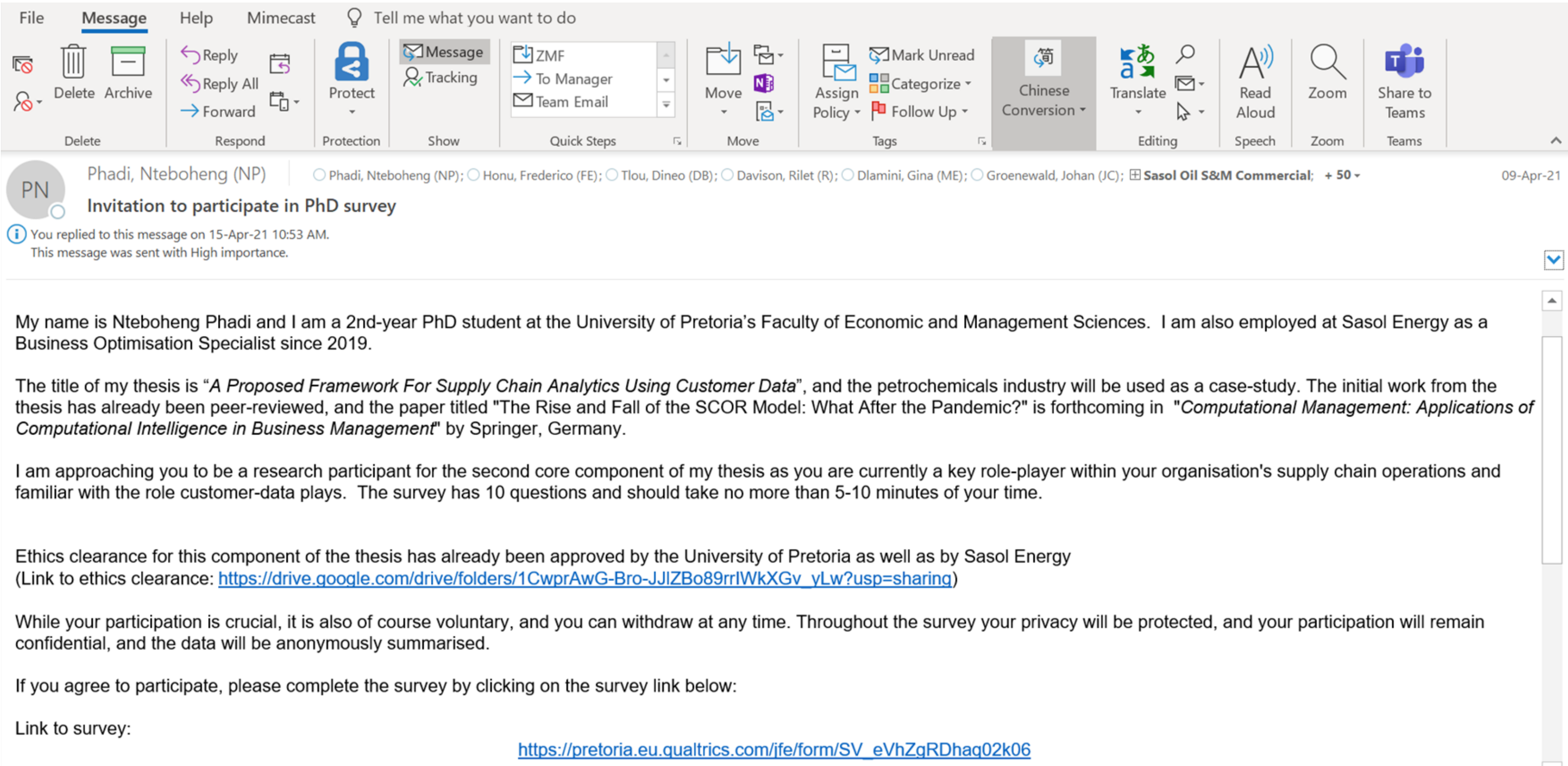
4 APPENDIX A: WEB-BASED SURVEY INVITE

The following is screen-grab of the email sent out for the survey sent out towards the aims of Chapter 3.



Phadi, Nteboheng (NP) | Phadi, Nteboheng (NP); Honu, Frederico (FE); Tlou, Dineo (DB); Davison, Rilet (R); Dlamini, Gina (ME); Groenewald, Johan (JC); **Sasol Oil S&M Commercial**; + 50 | 09-Apr-21

PN

Invitation to participate in PhD survey

You replied to this message on 15-Apr-21 10:53 AM.
This message was sent with High importance.

My name is Nteboheng Phadi and I am a 2nd-year PhD student at the University of Pretoria's Faculty of Economic and Management Sciences. I am also employed at Sasol Energy as a Business Optimisation Specialist since 2019.

The title of my thesis is "*A Proposed Framework For Supply Chain Analytics Using Customer Data*", and the petrochemicals industry will be used as a case-study. The initial work from the thesis has already been peer-reviewed, and the paper titled "The Rise and Fall of the SCOR Model: What After the Pandemic?" is forthcoming in "*Computational Management: Applications of Computational Intelligence in Business Management*" by Springer, Germany.

I am approaching you to be a research participant for the second core component of my thesis as you are currently a key role-player within your organisation's supply chain operations and familiar with the role customer-data plays. The survey has 10 questions and should take no more than 5-10 minutes of your time.

Ethics clearance for this component of the thesis has already been approved by the University of Pretoria as well as by Sasol Energy
(Link to ethics clearance: https://drive.google.com/drive/folders/1CwprAwG-Bro-JJlZBo89rrlWkXGv_yLw?usp=sharing)

While your participation is crucial, it is also of course voluntary, and you can withdraw at any time. Throughout the survey your privacy will be protected, and your participation will remain confidential, and the data will be anonymously summarised.

If you agree to participate, please complete the survey by clicking on the survey link below:

Link to survey:

https://pretoria.eu.qualtrics.com/jfe/form/SV_eVhZgRDhaq02k06

5 APPENDIX B: RANGE OF DATA SETS

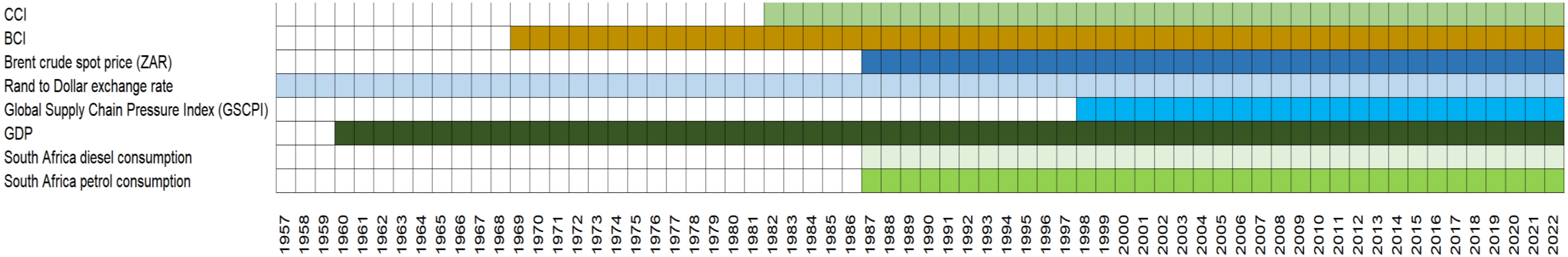


Figure 24: Range of Data Sets

6 APPENDIX C: ETHICAL CLEARANCE

The following is the clearance from the University of Pretoria Research Ethics Committee.

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

RESEARCH ETHICS COMMITTEE

Faculty of Economic and Management Sciences

Approval Certificate

5 February 2021

Ms NP Phadi
Department: Business Management

Dear Ms NP Phadi

The application for ethical clearance for the research project described below served before this committee on:

Protocol No:	EMS131/20
Principal researcher:	Ms NP Phadi
Research title:	A proposed framework for supply chain analytics using customer data
Student/Staff No:	29023051
Degree:	Doctoral
Supervisor/Promoter:	Prof S Das
Department:	Business Management

The decision by the committee is reflected below:

Decision:	Approved
Conditions (if applicable):	
Period of approval:	2020-11-02 - 2020-12-04

The approval is subject to the researcher abiding by the principles and parameters set out in the application and research proposal in the actual execution of the research. The approval does not imply that the researcher is relieved of any accountability in terms of the Codes of Research Ethics of the University of Pretoria if action is taken beyond the approved proposal. If during the course of the research it becomes apparent that the nature and/or extent of the research deviates significantly from the original proposal, a new application for ethics clearance must be submitted for review.

We wish you success with the project.

Sincerely

pp PROF JA NEL
CHAIR: COMMITTEE FOR RESEARCH ETHICS