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QUANTITATIVE BUSINESS MODEL AND SUPPLY CHAIN MANAGEMENT: EVIDENCE FROM A MULTINATIONAL ORGANIZATION IN NIGERIA

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Abstract

This study examines the application of quantitative business models (QBMs) in supply chain management, focusing on Nigeria's manufacturing industry. Grounded in Systems theory, the study uses a descriptive research design and questionnaire from 83 supply chain employees at Dangote Plc.'s Calabar depot. Hypotheses were tested with Generalized Linear Models Probit Regression. Results indicate that demand forecasting accuracy positively influences inventory management (β=.234; p>.05) and production planning enhances supply chain agility (β=.309; p>.05), though these associations were not statistically significant. The study concludes that while QBMs have a positive impact on supply chain performance, their influence is not significant. Recommendations include improving demand forecasting accuracy and production planning processes to enhance supply chain agility. This study provides empirical evidence supporting the relevance of QBMs in optimizing supply chain management in Nigeria's manufacturing sector.

Keywords: Demand forecasting accuracy, Evidence-driven production planning, Quantitative business models, Supply chain agility, Systems Theory

Introduction

In the contemporary business environment, organizations continuously seek to optimize operations and gain a competitive edge. A notable approach is employing quantitative business models to enhance supply chain management. Quantitative business models (QBMs) use mathematical and statistical methods to analyze and predict business outcomes, aiding decision-making in areas like production and sales (Andreevich, 2020). Successfully applied across finance, marketing, and operations, QBMs help minimize risks and maximize profits (Teti, Dell'Acqua and Bonsi, 2022). The intersection of QBMs and supply chain management (SCM) has drawn considerable interest as businesses leverage advanced analytics and data science techniques to optimize their supply chains. In supply chain management, QBMs optimize inventory, demand forecasting, production planning, and logistics (Tadayonrad and Ndiaye, 2023). This coordination involves managing the movement and storage of materials and products from origin to consumption, aiming to reduce costs and enhance customer satisfaction.

The complexity of modern business operations, driven by e-commerce and globalization, necessitates data-driven decision-making. QBMs can streamline supply chain operations, reduce costs, and improve customer satisfaction. Strategies include demand forecasting algorithms (Kumar, Ozdamar and Zhang, 2018), linear and nonlinear programming formulations (Tiwari and Darbari, 2019), system dynamics simulations (Sterman, 2000), and data-driven predictive analytics approaches (Papanagnou, Seiler, Spanaki, Papadopoulos and Bourlakis, 2022). Despite their proven effectiveness, there is limited research on QBM application in supply chain management within emerging economies.

This gap is significant for multinational companies in emerging economies like Dangote Plc, which operates an extensive supply chain across Africa and faces market uncertainties typical of emerging economies. Operating in Nigeria, with its high market uncertainty, organizations face substantial market uncertainties and inefficiencies. The business environment is characterized by inconsistent policies and inadequate infrastructure, introducing risks and complexities that complicate demand forecasting. Quantitative forecasting tools that consider political and economic variables could mitigate these risks. In Nigeria, logistics and transportation are costly and unreliable due to poor infrastructure and insecurity, significantly increasing supply chain costs. This scenario underscores the need for optimization techniques that evaluate routing and modality options.

Additionally, Nigeria's developing economy faces issues like inflation, exchange rate volatility, and high lending rates, making quantitative business models for production planning and risk assessment critical for navigating such an uncertain environment. Accordingly, the firm, founded in 1977 in Lagos, Nigeria and established in 1981, has an expansive supply chain which is significantly exposed to the market uncertainty that characterize emerging economies (Marques, Erthal, Schott and Morais, 2021). The attendant information deficit introduces elements of risks that obscure the management of supply chain networks. So, the gap in extant research provides a hinderance to the capacity of such organizations to fully leverage the potential of quantitative techniques and effectively address its supply chain challenges.

Since existing research has not thoroughly addressed the application of QBM proxies, such as demand forecasting techniques, inventory management strategies, and production planning to enhance SCM processes of organizations in Nigeria, including procurement, logistics management, inventory management, and supply chain agility, the study aims to empirically evaluate the impact of quantitative business model implementation on key supply chain performance indicators in the cement industry. Focusing on Dangote Group PLC, the study highlights the research gap regarding the empirical evaluation of quantitative business models on real supply chain performance across different industry contexts. The findings may offer valuable insights into utilizing quantitative business models to manage supply chains in emerging markets.

Objectives of the Study

The aim of the study is to examine the application of quantitative business model in supply chain management with a view to providing theoretical, practical and policy-driven insights that direct effective supply chain performance. The specific objectives of the study are as follows:

i. To determine the effect of demand forecasting algorithms on inventory management across different product categories.

ii. To ascertain the effect of production planning on supply chain agility.

Conceptual Review and Conceptual Framework

Demand forecasting is crucial for business model design and supply chain optimization, involving the prediction of future customer purchases (Ghalehkhondabi et al., 2017). Accurate forecasts balance supply and demand, reducing risks of overproduction (excess inventory costs) and underproduction (stockouts and lost sales). They guide efficient allocation of labor, materials, production capacity, and distribution resources, enabling businesses to adapt to demand fluctuations (Liu et al., 2022). Optimized forecasting positions inventory strategically and optimizes transportation routes, minimizing costs and waste (Liu et al., 2020). Additionally, forecasts inform revenue projections, essential for budgeting and financial decisions (Pereira and Cerqueira, 2022).

Understanding demand factors is vital for informed decisions. Techniques like time series analysis, causal models, expert opinions, forecast combinations, and diffusion models deconstruct demand patterns (Ciaburro, 2022). Time series analysis uses historical patterns to predict future demand, while causal models link demand with factors like price and seasonality (Song et al., 2023). Expert opinions are useful in data-scarce environments, leveraging domain-specific knowledge (Mauksch et al., 2020). Enhancing accuracy involves combining multiple forecasting models through simulation, improving robustness and supporting strategic decisions (Pinçe et al., 2021). However, these methods raise concerns about interpretability, operability, and potential biases, particularly in developing economies. This study examines these aspects within the context of inventory management.

Early research on inventory management focused on optimizing inventory levels by balancing holding costs with the risk of stockouts (Friday et al., 2021). Classic models like Economic Order Quantity (EOQ) provided a framework for minimizing total inventory costs. As the field matured, more complex scenarios involving demand uncertainty, lead times, and multiple supply chain echelons were studied. Stochastic models and simulation techniques became key tools for analyzing these systems and developing optimal inventory policies (Goldberg, Reiman, and Wang, 2021).

Contemporary research, driven by technological advancements, continues to evolve. Effective inventory management is crucial for optimizing operations, reducing costs, and ensuring customer satisfaction. It involves balancing adequate stock levels to avoid stockouts and excess inventory. Stockouts lead to lost sales and damaged customer relationships, while excess inventory incurs unnecessary holding costs (Vergara et al., 2021; Halilović, 2022). Optimal order quantities must consider lead time, demand variability, and supplier constraints (Sarkar et al., 2022). Accurate demand forecasting is essential for optimizing inventory levels, reducing stockout and overstocking costs (Armenzoni et al., 2015). High demand variability may require advanced forecasting techniques like machine learning, while stable demand can be forecasted using simpler methods. Despite its importance, there is limited research on forecasting techniques used by organizations in Nigeria, a market characterized by a large population, rapid urbanization, and growing consumer demand. Investigating these techniques and their impact on inventory performance is crucial for improving inventory management in Nigeria.

Production planning is a core element of operations management, focusing on efficiently converting materials and labor into finished goods (Baxter, 2018). It involves mathematical and analytical techniques to optimize decisions on production quantity, timing, inventory management, and supply chain coordination. Early foundational techniques were established by Jones (1967), while Whybark and Williams (1976) pioneered materials requirements planning (MRP) to align material needs with the master production schedule

(MPS), balancing capacity and demand through time-phased plans (Koh, Saad, and Jones, 2002).

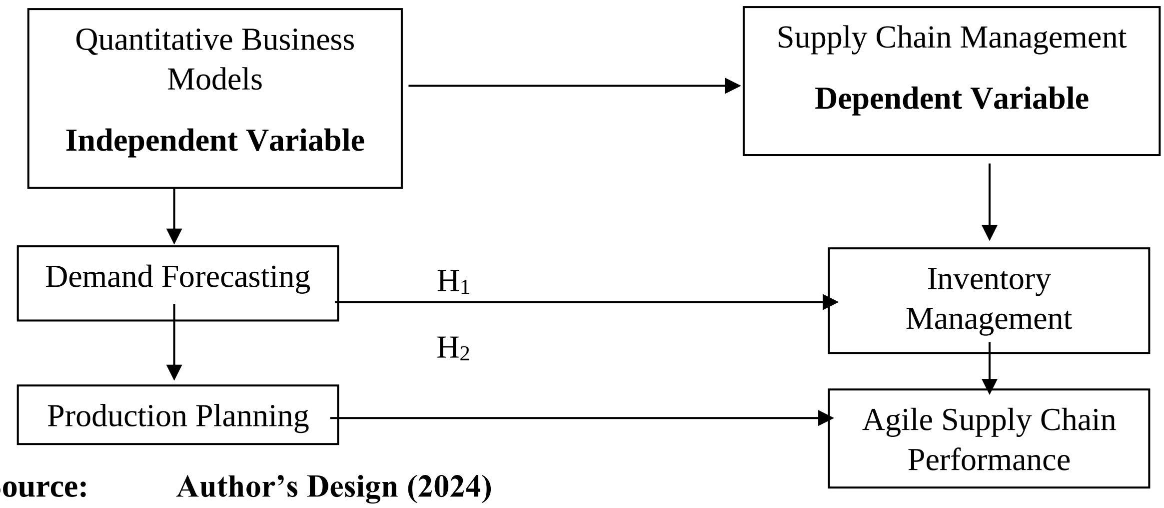
Research evolved to include capacity planning approaches: optimization models for job scheduling and resource allocation (Missbauer and Uzsoy, 2011), simulation for decision-making under uncertainty (Østergård, Jensen, and Maagaard, 2016), and performance tracking to compare actual output to plans (Zhen, Huang, and Wang, 2019). Effective production planning is crucial for agile supply chain management. While extensive research exists on production planning and agile supply chain management in developed economies, studies in emerging economies are limited (Oliveira-Dias, Moyano-Fuentes, and Maqueira-Marín, 2022). Nigeria, as Africa's largest economy, offers a unique context to explore this link. Its rapid growth, large population, and increasing demand for goods create a dynamic environment requiring agile and responsive supply chains.

Supply chain agility has gained prominence due to the increasing dynamism and complexity of the global business environment. Key dimensions contributing to its effectiveness include resilience, flexibility, strategic alignment, and customer responsiveness (Cabrita et al., 2023). Supply chain resilience is the ability to withstand and recover from disruptions like natural disasters, economic crises, or supplier failures, achieved through diversified supplier networks, risk management strategies, and contingency plans (Ivanov, 2022). Flexibility involves adapting to market conditions and customer demands by adjusting production volumes, modifying product specifications, and shifting sourcing strategies using modular designs and flexible manufacturing processes.

Strategic alignment ensures coordination among suppliers, manufacturers, distributors, and retailers through effective information sharing and joint planning. Customer responsiveness includes offering a wide range of products, customized solutions, and timely delivery. While these dimensions are widely acknowledged, the literature has limitations, especially in the Nigerian context. There is an overemphasis on technology's role in enabling agility, which may not apply due to limited tech adoption in Nigeria. The significant role of the informal sector and challenges like poor infrastructure and unreliable energy supply are often overlooked. Moreover, there is a gap in exploring the link between production planning and supply chain agility in Nigeria.

The literature lacks research on how production planning can be integrated with supply chain management practices to achieve agility in Nigeria's unique context and which production planning decisions can enable this agility. The investigation of these relationships in the study area follows from extant literature and these empirical findings directed the development of the conceptual framework in Figure 2.1.

Figure 2.1: Conceptual Framework



Source: Author's Design (2024)

Figure 2.1 is the conceptual framework of the study as elicited from the review of the concepts that make up the independent and dependent variables. The conceptual review suggests that quantitative business models are proxied by demand forecasting and production planning, while supply chain management is proxied by inventory management and agile supply chain performance. The study follows the elucidations and delineations of these concepts to examine how they are linked in the study area, using Dangote Group plc. as a case study. Before proceeding with the investigation, a theoretical framework was presented as the foundation for our hypothesis development.

Research Gap

The extant literature on quantitative business models and supply chain management was reviewed. These works established foundational techniques for demand forecasting, production planning and inventory management. Subsequently, empirical studies evaluated impacts on metrics like responsiveness, flexibility and fill rates. More recent contributions increasingly recognize the complex, interconnected nature of modern supply chains. Systems approaches optimize interfaces and information flows across functions. Contingency perspectives tailor quantitative methods to contextual factors.

Prior studies examine discrete elements such as forecasting or transportation optimization separately, but this study took a holistic approach to identify system-wide QBM applications such as production planning and supply chain agility to capture the complexities that characterize an emerging market like Nigeria. Also, while linear programming is common, real-world supply chains in obscure markets are characterized by non-linear aspects, and as a result, there is limited research evidence on data-driven strategies to advance theory and practice at the intersection of quantitative models, supply chain management and multinational operations in an emerging market context.

A careful perusal of extant literature indicates that existing research often relies on global models that may not be directly applicable to the Nigerian context. Succinctly, despite the growing importance of supply chain agility in today's competitive business environment, there is a scarcity of studies that have investigated the role of demand forecasting and production planning in achieving agility in Nigerian supply chains. This gap is particularly concerning given the unique challenges faced by Nigerian organizations, including inadequate infrastructure, high levels of uncertainty, and rapid growth.

The consequences of not addressing this gap are far-reaching. Without effective demand forecasting and production planning, Nigerian organizations are likely to experience stockouts, overstocking, and inefficient inventory management, leading to increased costs, reduced customer satisfaction, and decreased competitiveness. Furthermore, the lack of agility in supply chains can lead to reduced responsiveness to changing market conditions, making it difficult for organizations to adapt to shifting customer needs and preferences. On the other hand, addressing this gap can have numerous benefits. Developing and applying demand forecasting and production planning models that are tailored to the Nigerian context may help organizations improve their inventory management practices, reduce costs, and enhance customer satisfaction through supply chain responsiveness. Thus, it is essential for further research on the application of demand forecasting and production planning in inventory management and supply chain agility in Nigeria to develop and test quantitative business models that can be used to improve organizational performance.

Methodology

The study used a descriptive research design with a survey method to examine the relationship between quantitative business models and supply chain management. Conducted in Calabar, Nigeria, home to one of Dangote Plc's largest cement production facilities, the location provided ample supply chain data for analysis. Calabar's strategic importance made it ideal for evaluating quantitative tools for routing, facility location, and fleet management planning. Data were collected from 83 senior supply chain management employees at Dangote Plc's Calabar depot using a structured questionnaire. A total enumeration method was used due to the manageable population size. Data were analyzed using Generalized Linear Models (GLM) Probit Regression Analysis, suitable for the dichotomous dependent variables, such as fill rates and on-time deliveries. Statistical significance was set at $p<0.05$, following widely accepted practices in operations and supply chain studies (Goh et al., 2021; Greene, 2012; Wang and Zhao, 2021).

Data Presentation and Analysis

Objective One

Higher demand forecasting accuracy positively influences inventory management by Dangote Group Plc. The regression model is described as follows in Equation I:

$$FillRate_{it} = \beta_0 + \beta_1 ForecastAccuracy_{it} + \beta_2 LogisticsCost_{it} + \beta_3 SeasonalityDummy_{it} + \beta_4 ProductDummy_i + \mu_i + \lambda_t + \varepsilon_{it} \quad (I)$$

Where: FillRateit is the inventory fill rate (1/0) for unit i in period t, ForecastAccuracyit is the demand forecasting accuracy score, LogisticsCostit controls for fluctuations in transportation costs, SeasonalityDummyit controls for seasonal demand patterns, ProductDummyi controls for product category fixed effects, μi represents unit fixed effects, λt represents time fixed effects

εit is the error term. Following the model, generalized linear model probit regression results are presented as follows.

Parameter Estimates

Parameter	B	Std. Error	95% Wald Confidence Interval		Hypothesis Test			Exp(B)	95% Wald Confidence Interval for Exp(B)	
			Lower	Upper	Wald Chi-Square	df	Sig.		Lower	Upper
(Intercept)	-1.500	.6788	-2.831	-.170	4.883	1	.027	.223	.059	.844
DemForecast	.234	.1642	-.088	.556	2.026	1	.155	1.263	.916	1.743
(Scale)	1[a]									

Dependent Variable: Inventory Management

Model: (Intercept), DemForecast

a. Fixed at the displayed value.

The GLM probit regression result for inventory management as the dependent variable and demand forecast as the independent variable shows the β value of 0.234 for Demand Forecast, suggesting an increase in the dependent variable with a one unit increase in the independent variable, holding all other variables constant. However, the p-value for 'Demand Forecast' (0.155) is greater than the typical significance level of 0.05, therefore we cannot say it makes a statistically significant unique contribution to the model. As a result, higher demand forecasting accuracy positively influences inventory management by Dangote Group Plc (β=.234; *p>.05*).

Objective Two

Effective production planning increases the likelihood of agile supply chain performance by Dangote Group Plc. The regression model is described as follows in Equation II:

$$AgilePerfomit = \beta0 + \beta1PlanningScoreit + \beta2SupplierReliabilityit + \beta3TechnologyInvestmentit + \beta4MarketTurbulenceit + \mu i + \lambda t + \varepsilon it \quad (II)$$

Where: AgilePerfomit is the agile supply chain performance measure (1/0), PlanningScoreit is the production planning effectiveness score, SupplierReliabilityit controls for supply reliability issues, TechnologyInvestmentit controls for investments in advanced technologies, MarketTurbulenceit controls for external market volatility, μi represents unit fixed effects, λt represents time fixed effects, εit is the error term. Following the model, generalized linear model probit regression results are presented as follows. The regression results are presented accordingly.

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp(B)	Lower	Upper
(Intercept)	-2.592	1.4018	-5.339	.156	3.418	1	.064	.075	.005	1.169
ProPlg	.309	.3037	-.286	.904	1.036	1	.309	1.362	.751	2.470
(Scale)	1[a]									

Dependent Variable: Agile SC Performance

Model: (Intercept), ProPlg

a. Fixed at the displayed value.

The parameter estimates Table provides the unstandardized regression coefficients (β) for the intercept and ProPlg (production planning) predictor, as well as the associated standard errors and significance values. For Production Planning, the positive β value indicates a positive relationship with Agile SC Performance. However, the relationship is not statistically significant based on the p-value exceeding the typical .05 threshold. The Exp(β) column represents the antilog of the β value, or odds ratio. An odds ratio greater than 1 for production planning suggests it is associated with higher odds of higher Agile SC Performance, but again this is not statistically significant. Consequently, production planning has a positive relationship with supply chain agility in Dangote Group Plc (β=.309; $p>.05$).

Discussion of Findings

Our findings indicate that while quantitative business models (QBMs) are used in Dangote Group Plc.'s supply chain management, they are not significant predictors of performance. This aligns with Systems Theory, highlighting the interdependency of QBMs and supply chain operations. Regarding objective one, our study supports El Jaouhari et al. (2022), showing that demand forecasting enhances inventory productivity and efficiency. For objective two, our results partially agree with Sriyakul et al. (2019); both studies find that production planning aligns with supply chain agility but differ on the significance of this alignment. Similar to Lalmazloumian et al. (2016), we confirm associations between variables, though our results do not show significant relationships.

Summary of the Findings, Conclusion, and Recommendations

The findings show that quantitative business models (QBMs) positively influence supply chain management performance at Dangote Group Plc., though the association is not statistically significant (β=.234, $p>.05$; β=.309, $p>.05$). This could mean the model doesn't fit the data or accurately reflects reality. A robustness test confirmed the model's good fit, with low values for Goodness of Fit, Deviance, and Pearson Chi-Square, and Scaled Deviance and Scaled Pearson Chi-Square values close to 1. Moderate AIC, AICC, and BIC values indicate the model with 'ProPlg' (production planning) fits better than a null model. These results suggest the model is robust and accurate. Thus, the positive but not significant association likely reflects reality. This means QBMs enhance supply chain performance, but Dangote Group Plc.'s supply chain would not significantly underperform without them. In conclusion, QBMs are beneficial for Dangote Group Plc.'s supply chain management, even if not significantly so.

The study suggests that multinational organizations in the area should improve demand forecasting accuracy using techniques like exponential smoothing, causal models, and machine learning algorithms. Leveraging supply chain analytics, including data mining and predictive modelling, can provide deeper insights into customer demand patterns and optimize supply chain operations. Accurate demand forecasting will enhance inventory management and customer satisfaction. Strengthening and aligning production planning processes across functions is crucial for enhancing supply chain agility. Adopting techniques such as lean manufacturing and flexible capacity management is recommended to navigate the volatile market environment. Additionally, regular training programs are advised to build internal capacity and expertise in quantitative supply chain management techniques, promoting best practices and continuous improvement.

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