Impact of Exogenous Variables on AI/ML Predictive Algorithm Prophet, in the FMCG Industry

by
Ryan Justin Anthony Rocke
BSc, Mechanical and Manufacturing Engineering, The University of the West Indies

and
Lili Zhang
BEng, Automation, Southwest Petroleum University

SUBMITTED TO THE PROGRAM IN SUPPLY CHAIN MANAGEMENT
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF APPLIED SCIENCE IN SUPPLY CHAIN MANAGEMENT
AT THE
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

May 2024

Signature of Author: ____
Ryan Justin Anthony Rocke
May 10th, 2024

Signature of Author: ____
Lili Zhang
May 10th, 2024

Certified by: ____
Dr. Ilya Jackson
Postdoctoral Associate
Capstone Advisor

Certified by: ____
Dr. María Jesús Sáenz
Executive Director, MIT SCM Master Programs
Capstone Co-Advisor

Accepted by: ____
Prof. Yossi Sheffi
Director, Center for Transportation and Logistics
Elisha Gray II Professor of Engineering Systems
Professor, Civil and Environmental Engineering

ACKNOWLEDGMENTS

We would like to extend our deepest gratitude to all those who provided their support and contributed to the success and completion of this Capstone project. First and foremost, we express our sincerest appreciation to our families: **Alisa S., Siyuan Li, Christophe P., Alexander J., Bagheera, Kiara, Wai Xiao** and **Si Xiao**. Without you, we would not have had the strength nor perseverance to pursue and complete this journey. Your unwavering faith and encouragement were our guiding lights during challenging times.

To our advisors, **Dr. Ilya Jackson** and **Dr. María Jesús Sáenz**, it was a privilege working under your esteemed leadership. MIT is renowned because of visionaries like you, who naturally inspire, drive innovation, and ultimately push to go above and beyond expectation. Thank you for showing us a snippet of excellence and being that example that lays foundation so that one day, we too understand what it takes to give back and lead budding supply chain enthusiasts of the future.

A very special thank you to **Charles 'Chuck' Yee,** the MIT SuperCloud team, and Lincoln Laboratory Supercomputing Center team, without whom we would not have the HPC resources to conduct the in-depth and extended list of experiments. And finally, a big thank you to **Dr. Elenna Dugundji** and **Dr. Thomas Koch**, who's steadfast support, even with the many layers of red tape, were invaluable in nudging the project along, especially at roadblocks.

"One looks back with appreciation to the brilliant teachers, but with gratitude to those who touched our human feelings. The curriculum is so much necessary raw material, but warmth is the vital element for the growing plant and for the soul of the child."

- Carl Jung

Thank you!
Ryan and Lili

Impact of Exogenous Variables on AI/ML Predictive Algorithm Prophet, in the FMCG Industry

By
Ryan Justin Anthony Rocke

and
Lili Zhang

Submitted to the Program in Supply Chain Management on May 10th, 2024
in Partial Fulfillment of the Requirements for the Degree of Master of Applied Science
in Supply Chain Management.

ABSTRACT

As Artificial Intelligence (AI) and Machine Learning (ML) continue to advance, their application in supply chain demand forecasting has surged, significantly impacting the field. These ML techniques improve forecasting accuracy, ultimately supporting managerial inventory and planning decisions. In this project, we evaluate the underlying hypothesis that suggests the application of targeted exogenous variables as model features, would further improve the predictive accuracy of the popular ML algorithm "Prophet". Provided with statistically normalized Fast Moving Consumer Goods (FMCG) sales data from the Indian Subcontinent, <u>we investigated 5,184 data points from 2011 to 2023 across 36 products</u>. We screened and shortlisted exogenous variables within economic, health, climate, and political areas and selected 10 for evaluation in the predictive model. Each product was cross-validated with variables built as univariate regressors (features), and it was found that the introduction of exogenous variables reduced the Mean Average Percent Error (MAPE) by as much as -40.93%. Furthermore, incorporating targeted exogenous variables together with Hyper-Parameter tuning (calibration), had astounding results, with <u>MAPE decreases by as much as -143.48%</u>. This study proves targeted exogenous variables beneficial for practical application in improving forecasting accuracy within the FMCG industry.

Capstone Advisor: Dr. Ilya Jackson
Title: Postdoctoral Associate

Capstone Co-Advisor: Dr. María Jesús Sáenz
Title: Executive Director, MIT SCM Master Programs

TABLE OF CONTENTS

1. INTRODUCTION

1.1. Background and Motivation

Demand forecasting represents a significant challenge for managerial decision-making since it serves as a crucial input for both operational and strategic decisions (van Donselaar, Vishal, van Woensel, Broekmeulen, & Fransoo, 2010). An accurate demand forecast is incredibly useful to business management in an ever-changing market. A robust demand forecast not only helps companies effectively plan their supply chain and manage inventory but also supports the financial department in cash flow management. Additionally, it assists marketing and sales departments with pricing strategies. Strategically, reliable forecasting provides management with critical metrics that are essential for fostering company growth. Within Supply Chains, demand forecasting is the basis for many managerial decisions (Abolghasemi, Beh, Tarr, & Gerlach, 2020) as its accuracy can have a significant impact on business activity and enterprise performance. It is one of the business processes benefiting from advancements in Artificial Intelligence (AI) and Machine Learning (ML) technologies. McKinsey's report highlights the clear advantage AI/ML algorithms have over traditional spreadsheet-based analytic methods with the potential to diminish errors by 20% to 50% and product shortages by 65% (Amar, Rahimi, Surak, & Bismarck, 2022). Given demand forecasting's critical role in the industry application, what additional steps can be taken to enhance the performance of the AI/ML forecasting methods? The key factors influencing forecasting accuracy are prediction uncertainty and the length of time horizon (Revilla, Sáenz, Seifert, & Ma, 2023). In our study, we introduced the exogenous factors. Fast-Moving Consumer Goods (FMCG) industry is known for its quick turnover, large Stock Keeping Unit base (SKU), and susceptibility to exogenously influenced consumer behavior. Understanding the impact of exogenous factors is of great significance for demand forecasting. However, research on exogenous factors' impact on AI/ML predictive algorithms, particularly in the FMCG industry, has been scarce. A literature gap was also identified, considering the limited number of relevant case studies in academic literature.

Within Supply Chains, demand forecasting is the basis for many managerial decisions (Abolghasemi, Beh, Tarr, & Gerlach, 2020) as its accuracy can have a significant impact on business activity and enterprise performance. It is one of the business processes benefiting from advancements in Artificial Intelligence (AI) and Machine Learning (ML) technologies. McKinsey's report highlights the clear advantage AI/ML algorithms have over traditional spreadsheet-based analytic methods with the potential to diminish errors by 20% to 50% and product shortages by 65% (Amar, Rahimi, Surak, & Bismarck, 2022). Given demand forecasting's critical role in the industry application, what additional steps can be taken to enhance the performance of the AI/ML forecasting methods? The key factors influencing forecasting accuracy are prediction uncertainty and the length of time horizon (Revilla, Sáenz, Seifert, & Ma, 2023). In our study, we introduced exogenous factors.

The fast-Moving Consumer Goods (FMCG) industry is known for its quick turnover, large Stock Keeping Unit base (SKU), and susceptibility to exogenously influenced consumer behavior. Understanding the impact of exogenous factors is of great significance for demand forecasting. However, research on exogenous factors' impact on AI/ML predictive algorithms, particularly in the FMCG industry, has been scarce. A literature gap was also identified, considering the limited number of relevant case studies in academic literature.

1.2. Research Question

While AI/ML predictive algorithms have shown promise in demand forecasting, there may be an opportunity to improve accuracy by better understanding their response to exogenous variables. This leads us to the following defined Research Question: *"How can exogenous variables improve AI/ML forecasting in the Fast-Moving Consumer Goods (FMCG) industry?"*

To address this research question, we set up three objectives, which are as follows: (1) Identify key exogenous variables relevant to FMCG demand forecasting. (2) Assess how different configurations of the AI/ML algorithm "Prophet" are affected by these exogenous variables and impact the model's overall accuracy. (3) Develop strategies and recommendations for businesses better to integrate exogenous variables into their Prophet forecasting model.

1.3. Approach

Prior to the integration of exogenous variables into the AI/ML predictive algorithm, data and model preparation are essential. In this study, we will use sales data from FMCG company operating in the Indian market. At the same time, we will shortlist the exogenous variables covering economics, health, climate, and politics areas. We will clean for both demand datasets and exogenous variables datasets before any model processing.

Regarding the AI/ML forecasting models, we will choose Prophet as our forecasting model. To assess the performance of the forecasting models more effectively, we will employ Mean Absolute Percentage Error (MAPE) as the metric for forecasting error while defining the preliminary Prophet script model for benchmarking and refine execute univariate batch parallel.

In addition to exploring the different impacts of exogenous factors on the model's performance, we will also incorporate different configurations to better fit the model, as well as work with to tune the hyperparameters of the model to achieve the best results.

2. LITERATURE REVIEW

In many supply chains, companies that are positioned at the upstream level are affected by the amplification of variance due to the distorted demand information that propagates through the multi-tiered supply chain network, leading to operation inefficiencies. Previous studies indicate that the application of sophisticated demand forecasting methods, like machine learning, could mitigate the effect and improve performance (Feizabadi, 2022).

In the realm of demand forecasting, machine learning (ML) has ushered in techniques that have revolutionized the practice. Compared to traditional methods such as Moving Averages, Exponential Smoothing, and Regression, many contemporary ML techniques have been gaining traction due to their innate ability to add and combine layers of complexity to the domain.

Time series analysis, particularly with Recurrent Neural Networks (RNNs), is a prevalent approach for capturing sequential dependencies and predicting demand fluctuations over time, as "it can match pattern through time that extends further than the provided current time window" (Carbonneau, Laframboise, & Vahidov, 2008). Ensemble learning techniques, such as

Random Forests and Gradient Boosting, have also gained prominence for their ability to combine multiple models, mitigating overfitting risks and improving overall forecasting reliability. Overall, deep learning models excel in handling non-linear patterns and are increasingly applied for demand prediction.

There is research that utilizes these approaches, looking at over six years of historical data across 330 products. Their paper resembles our study as they factored the impact of exogenous factors such as meteorological and COVID-19-specific data into their analysis (Nasseri, Falatouri, Brandtner, & Darbanian, 2023). Our study, which utilizes twelve years of sales data, is supported by a robust database. It addresses the gap in understanding how exogenous factors affect demand within the FMCG industry. Additionally, our use of the Prophet model sharpens the focus and direction of our research.

2.1. FMCG Demand Forecasting

In supply chain management, demand forecasting directly impacts production planning, order fulfillment, inventory control and purchasing strategy. Companies use predictive techniques to estimate sales and optimize costs. Accurate and reliable demand forecasts provide vital intelligence for supply chain managers to support their planning and decision making (Abolghasemi, Beh, Tarr, & Gerlach, 2020). According to a paper by the McKinsey Global Institute, "In consumer goods, supply-chain management is the key function that could benefit from AI deployment. Among the examples in our use cases, we see how forecasting based on underlying causal drivers of demand rather than prior outcomes can improve forecasting accuracy by 10 to 20 percent, which translates into a potential five percent reduction in inventory costs and revenue increases of two to three percent." (Chui , Henke, & Miremadi, 2019). Demand forecasting runs through the entire process of Sales and Operation Planning (S&OP), thereby affecting a company's financial performance. Therefore, accurate demand forecasting becomes crucial not only for the supply chain management but also for the company's operation.

The FMCG sector is known for products with short life cycles, high turnover rates, and a highly competitive market landscape. In the FMCG industry, market conditions and consumer preferences can change swiftly. Real-time data analysis and interpretation is needed. Demand in the FMCG industry is significantly influenced by seasonal trends and promotional activities. Meanwhile, considering the complex consumer behavior and fast reaction of shelf management, In this circumstance, demand forecasting for the FMCG industry is even more challenging (Aichner & Santa, 2023). The use of machine learning techniques facilitates the rapid analysis of large databases. Advanced analytics enable FMCG companies to predict sales figures by analyzing historical, behavioral, geographic, microeconomic, and demographic data, which are difficult to standardize in traditional methods.

The FMCG industry generates a large volume of complex data. It seems to be almost impossible for FMCG companies to use their entire data and turn it into an advantage, however, AI has the advantage of analyzing the data quicker and more accurately.

2.2. Time Series Forecasting

The practice of forecasting encompasses the comprehensive and dynamic process of making predictions about future trends (Syntetos, Babai, Boylan, Kolassa, & Nikolopoulos, 2016). It involves defining forecasting objectives, collecting historical data, selecting suitable forecasting methods, and refining predictions. This holistic approach requires collaboration, domain knowledge, and continuous improvement, adapting to changes in data patterns and external influences.

Within the broader practice, a forecasting model serves as a structured framework designed to formalize the prediction process. These models can range from simple to complex, "moving average, to the most refined, such as exponential smoothing with trend and seasonality correction" (Rizzi, 2022). Models can also employ various mathematical or computational methods tailored to the characteristics of the data and the nature of the forecasting task. Furthermore, forecasting models, which often involve algorithms and statistical techniques, give the user "an opportunity to evaluate the quality of the forecast" (Snyder & Shen, 2019). The effectiveness of the overall forecasting practice is closely tied to the selection, application, and refinement of these models, attempting to capture the underlying patterns in the historical data accurately.

Forecasting facilitates data-driven decision-making, promoting strategic operations and ultimately improving customer service and satisfaction. Due to this impact, forecasting tends to hold weighted importance in the Supply Chain realm. By accurately predicting customer demand, organizations can optimize inventory levels, reduce carrying costs, and enhance overall efficiency. Forecasting guides production planning, resource allocation, and supplier relationships, fostering an agile and responsive supply chain. Good forecasting plans also contribute to risk mitigation by enabling contingency planning for potential disruptions.

2.2.1. Traditional Statistical Methods

There are three important traditional (conventional) statistical methods for time series forecasting (Spyros, Wheelwright, & Hyndman, 1998): ***Cumulative***, ***Naïve***, and ***Moving Average***. The time series forecasting methods have been further deformed and improved to cater to the different characteristics of the datasets outlined in the previous section. The traditional methods for time series forecasting are devised to forecast the future behavior of time series and, at the same time, help understand the underlying structure of the data (Cerqueira, Torgo, & Soares, 2019). Table 2.1 shows some most commonly used statistical methods for time series forecasting (Cerqueira, Torgo, & Soares, 2019).

Table 2-1

Commonly used statistical methods for time series forecasting

ARIMA	The Auto-Regressive Integrated Moving Average model (Hyndman et al., 2018)
THETA	Equivalent to simple exponential smoothing with drift (Nikolopoulos, 2000)
ETS	The exponential smoothing state-space model (Gardner & Everette, 1985)
TBATS	An exponential smoothing state space model with Box-cox transformation, ARMA errors, trend and seasonal components (De Livera, Hyndman, & Snyde, 2011)

2.2.2. Machine Learning Methods

In statistical forecasting, the model learns from predefined parameters and estimates a linear regression analysis. In the case of independent variables and the dependent variables are nonlinear, involving multiple explanatory variables, machine learning steps in as a robust tool for uncovering valuable insights and estimating parameters (Syam & Sharma, 2018). Machine learning models are better for scalability, real-time implementation, and cross-validated predictive accuracy.

Machine learning methods in time series forecasting have been increasingly adopted to solve predictive tasks. A paper (Cerqueira, Torgo, & Soares, 2019) has argued that by using a learning curve method, machine learning methods improve the relative predictive performance as the sample size grows. Machine learning techniques are increasingly used to tackle univariate time series forecasting problems (Cerqueira, Torgo, & Soares, 2019). Table 2.2 lists some well-known machine-learning algorithms.

Table 2-2

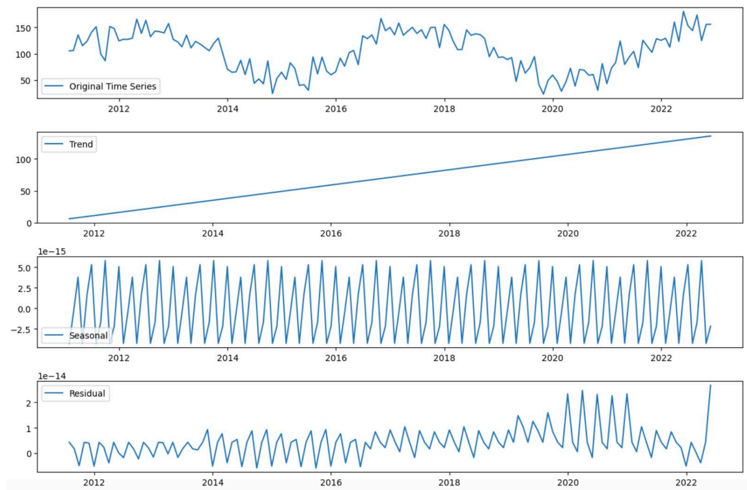
Example machine learning algorithms for time series forecasting

RBR	Rule-based model from Cubist R package (Kuhn, Weston, Keefer, & Coulter, 2014)
RF	Random Forest method, which is an ensemble of decision trees (Breiman, 2001)
GP	Gaussian Process regression (Karatzoglou, Smola, Ho, & Zeileis, 2004)
MARS	The multivariate adaptive regression splines (Friedman, 1991)

After the evaluation of those well-known machine learning algorithms, in our capstone project, we will target Prophet as our AI/ML predictive model. Facebook Prophet has not only excelled in various time series forecasting studies recently (Tianyu et al., 2022), but it also aligns well with our needs by examining the characteristics of our historical sales data to enhance the accuracy of our forecasts. Figure 2-1 shows an example of the time series component for one of our product data, which shows the seasonality, trend, and error characteristics, which fit well with the Prophet model’s algorithms. The Prophet model is employed to forecast data that exhibits seasonal variations, making it well-suited for analyzing our data with this model (Sivaramakrishnan, Fernandez, Babukarthik, & Premalatha, 2021). In section 2.2, we will illustrate more about the insight of the Prophet.

Figure 2-1

An example of the Time Series Components for SKU-Skincare1



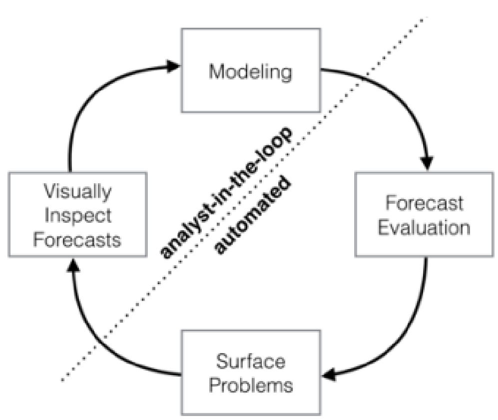
2.3. Prophet

Developed by the Meta Core Data Science Team and published in 2017, Prophet is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with seasonality (yearly, weekly, daily) and holiday effects. Classified as Meta Open Source, Prophet is implemented in programming languages R and Python and source code download links are housed in GitHub (GitHub, 2023).

It works best with time series that have strong seasonal effects and several seasons of historical data. It is robust to missing data and shifts in the trend, and typically handles outliers well (META - Core Data Science Team, 2017).

Figure 2-2

Analyst in-the-loop model (Taylor & Letham, 2017)



Although it can be used in a fully automatic way, Prophet is designed to be used in an analyst-in-the-loop, which allows for model tuning, enabling inspection, interpretation and adjustment based on the analyst's expertise in the domain (Figure 2-2).

Prophet is known for excelling in its simplicity and practicality and has a similar process flow to most Machine Learning time series models. A historical input (reference) data frame is loaded, the model, hyperparameters and regressors are then defined and the model is fit. From there, future predictions or cross-validations can take place, of which, we are interested in the latter for this project. Similar to a Generalized Additive Model (GAM) (Hastie & Tibshirani, 1987), Prophet in its core form uses a decomposable time series model (Peters, 1990) with components: trend, seasonality, holidays and residual. They are combined as noted in the following equation:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon t \qquad (1)$$

Where $g(t)$ stands for trend of time series over a non-periodic period.

$s(t)$ stands for seasonality which stands for weekly or yearly.

$h(t)$ stands for holidays for potential non-stationary holidays in the time series.

$\varepsilon(t)$ stands for error term or residual term (Gaussian distribution).

Noted within the original whitepaper, and a feature that we will be exploring is that the model uses (not) only time as a regressor but possibly several linear and non-linear functions of time as components (Taylor & Letham, 2017).

2.4. Exogenous Factors and Variables

Various factors affect the performance of demand forecasting, including the type of good (new products or existing products), market competition, customer seasonal demand, the price of the product, and economic development, etc. (Litvak, 2020). In our study, we categorize those influencing factors into two groups: endogenous factors, which are internal and defined by the business model, and exogenous factors, whose measure is determined outside the model and imposed on the model. For example, specific business models do not have the leverage to steer the overall macroeconomic landscape; in contrast, the economy does hold significant sway over consumer demand thereby affecting the model itself. In this example, economic trends are exogenous factors to the specific business model. We cannot control the exogenous factors influencing the business operation, but it's crucial to comprehend how these exogenous factors specifically affect the business context. In industry applications, understanding these dynamics enables the business owner to devise strategies and make adjustments that fortify the company's resilience (Leonard, 2018).

In many complex systems, we face the challenges of distinguishing between endogeneity and exogeneity and the relative effects of self-organization versus external impact. This is difficult in most physical systems because externally imposed perturbations may lie outside the complex attractors which itself may exhibit bifurcations (Sornette, Deschâtres, Gilbert, & Ageon, 2004).

Demand forecasting is subject to variability and is sensitive to a range of factors, including both endogenous and exogenous factors. Exogenous factors encompass broader macroeconomic indicators that greatly affect the accuracy of demand forecasting (Yasir et al., 2022). In our capstone, in addition to the macroeconomic indicators, we will also examine the influences of health, climate, politics, and economics.

The selection of appropriate exogenous factors is a vital step in our study. These factors must be chosen according to the specific features of the FMCG sales dataset. We will use a combination of intuitive reasoning, straightforward logic, and insights from existing research to identify potential exogenous factors. It's impractical to include every possible exogenous factor in our analysis, hence, we will prioritize and select the top ten which exert the most significant influence on our target dataset. These selected factors will then be transformed into corresponding time-series data, aligning them as exogenous variables with our sales data for use in our forthcoming experiment.

2.4.1. Gross Domestic Product (GDP)

GDP is the market value of the final goods and services produced in a country (Argandoña, 2017). It is a key indicator of the economic health of a country. A growing GDP suggests an expanding economy, which generally leads to increased consumer spending and higher demand for goods and services. It is one of the measurements of national income and output at a given period of time (Kira, 2013). There is an argument in the previous paper about the relationship between supply chain performance and GDP, both supply chain performance and GDP have significant associations with each other (Akkermans, Bogerd, Yücesan, & Wassenhove, 2003). GDP has a positive effect on supply chain performance, which includes demand forecasting in supply chain management.

2.4.2. Consumer Price Index (CPI)

Consumer Price Index (CPI) measure changes in the general level of prices of goods and services that households acquire for consumption over time. Initially introduced in many countries to gauge fluctuations in living costs for workers, CPIs help in adjusting wage increases to reflect changes in price levels (Graf, 2020). As per the statement in the Consumer Price Index Manual, a CPI can be used for a variety of purposes, especially for inflation targeting. Elements of a CPI are often based in the calculation of purchasing power, and the purchasing power, in other words, is correlated with consumer demand.

Inflation is a critical variable in macroeconomics, defined as the increase in the general price of goods over time. As the price of goods rises, the purchasing power of consumer decreases, adversely affecting the performance of supply chain activities related to goods (Sinaga, Saudi, & Roespinoedji, 2018).

2.4.3. Population

Expenditure patterns are thought to be shaped by price and income factors and household demographic characteristics. Therefore, changes in demographic dynamics in a country could have significant implications for its structure of production and income distribution (Ketkar & Ketkar, 1987). Previous studies have highlighted an intuitive link between a country's demographic profile and its demand for personal consumables. Generally, larger populations tend to drive greater demand for consumables. Despite there is intuitive understanding of the link between population size and demand for Fast Moving Consumer Goods (FMCG), we opted to include this exogenous factor in our capstone project to validate whether the AI/ML predictive model produces consistent results with our intuition.

By reviewing previous literature, we found that there is a conclusion showing the implications for the future trends in consumer expenditures: (1) An increase in education and female labor force participation would raise expenditure on food away from home, but that on food at home may stagnate. (2) Due to the decline in average family size and the increase in single-person families, the demand for rental housing could increase. (3) An increase in discretionary incomes, associated with falling family size, would raise demand for recreational goods and services. (4) An increase in female education and labor force participation could significantly increase the proportion of expenditures devoted to domestic service. (5) These very factors, however, may reduce the demand for women's and children's clothing (Ketkar & Ketkar, 1987).

Various dimensions can be explored regarding how shifts in population composition differentially influence consumer behavior. This research originates from the previous century; however, its findings remain relevant and have been repeatedly validated over time.

2.4.4. Supply Chain Disruptions

In addition to these long-term and continuous influence factors, disruptions are also a category of exogenous factors that we cannot get around, and in some literature are also referred to as exogenous shocks (Renold, Vollenweider, Mijovic, Kuljanin, & Kalic, 2023). As a special part of exogenous factors, supply chain disruptions and related issues are considered to be the most challenging issues facing companies competing in today's global marketplace (Revilla & Sáenz, 2013). In our example, COVID-19 is one of the exogenous shocks. COVID-19 being one of the most detrimental exogenous impacts, was simulated in the model as an exogenous shock. The erratic fluctuations in consumer behavior during COVID-19 have increased the difficulty of forecasting demand patterns, posing challenges to the adaptability and accuracy of AI/ML forecasting models (Jackson & Ivanov, 2023). Besides COVID-19, which is a source of natural hazards, there are three other risks of source for supply chain disruptions that can also be considered exogenous shocks they are market, supply chain discontinuity, and socio-economic (Revilla & Sáenz, 2013).

2.5. Forecasting Error Metrics

To address our research question, assessing and contrasting the accuracy of models' performance within different configurations (with or without exogenous variables) is necessary. This requires a quantifiable measure of accuracy, (of which) four metrics are commonly used to evaluate the forecast error (Hyndman, 2006). In looking at the various pros, cons and general applicability to our dataset, we decided to use the MAPE as the metric for assessing forecast error. The details are shown in Table 2-3. MAPE is the most used and simplest metric. The selection of MAPE is in light of the fact that the value is expressed as a percentage, making it appropriate for assessing the accuracy of a model (Pontoh et al., 2021). Table 2-4 shows a MAPE standard category for evaluation (Meade, 1983).

Table 2-3

List of forecasting error metrics (Hyndman, 2006)

Scale-dependent metrics	MAE	Suitable for assessing accuracy within the same series	**Strengths**: Easy to understand and compute. **Weaknesses**: Not suitable for comparison across different data series due to scale dependency
Percentage-error metrics	MAPE	Commonly used to compare forecast performance between different data series	**Strengths**: Allows comparison across different scales. **Weaknesses**: Can become infinite or undefined with zero values in the data
Relative-error metrics	MdRAE	Recommended for assessing forecast accuracy across multiple series	**Strengths**: Scale independent **Weaknesses**: Can become problematic with small errors or when the benchmark involves division by zero
Scale-free error metrics	MASE	Can be applied across different forecast methods and all types of series	**Strengths**: Avoids the infinite or undefined values problem **Weaknesses**: The potential limitation is when all historical observations are equal

Table 2-4

MAPE standard category for forecasting evaluation (Meade, 1983)

MAPE	Forecasting Criterion
<10%	Accuracy of forecasting is very good
10-20%	Accuracy of forecasting is good
20-50%	Accuracy of forecasting is enough good
>50%	Accuracy of forecasting is not good

3. METHODOLOGY

3.1. Data Selection and Imputation

3.1.1. Demand Data

Sales data from a prominent FMCG company was shared for a subsect of their Indian Sub-Continent operation. This dataset is comprised of 63 product (SKUs) across 10 product categories and a timeframe of monthly data from 2011 to 2023 (see Table 3-1

Initial Product (SKU) List).

Table 3-1

Initial Product (SKU) List

Product Category	Product (SKU) Count
Air	1
Baby Care	6
Blades razors	1
Fabric	12
Oral	6
Skin care	6
Female	6
Hair	6
Health care	9
Personal care	10

Datasets were shortlisted looking at date range, zero/blank native count, and number of outliers as criteria (summarized in Table 3-2

Product (SKU) Selection and Ranking Criteria). SKU's that fell in the Tier 1 category were kept and used as the product (SKU) base for the project, whereas Tier 2 and Tier 3 were classed as disqualified and eliminated from the project.

The data classification reduced the need to address data inconsistencies, especially in Tier 1 class. However, where needed, blanks, outliers, and errors were imputed with a univariate back or forward fill imputation method.

Table 3-2

Product (SKU) Selection and Ranking Criteria

Class	Product (SKU) Count	Notes	Available Data Points (Months)	Zero or Blank Count (%Tot)	Outlier Count (%Tot)
Tier 1	36	Used for project	144	<1	<10%
Tier 2	3	Eliminated from Project Scope	>120	1> & <10	<10%
Tier 3	26	Eliminated from Project Scope	<120	N/A	N/A

3.1.2. Exogenous Data

The CEIC database is recognized for providing extensive and reliable economics, industry, and finance time-series data (CEIC, 2023). Using such a reputable source ensured that our analysis was based on dependable and up-to-date information, which was essential for making accurate forecasts and reliable analysis. Of particular importance was gathering time-series data that aligned with the timeframe of our history of sales data. Therefore, we require that our exogenous variables data span from 2011 to 2023 and was transformed into monthly data to maintain consistency in our comparative analyses. Given that our predictive target data pertains to India, we aimed to geographically constrain the exogenous variables data to the Indian region as well. This approach helped ensure that the data's relevance and impact were maximized for the geographic context under consideration.

As previously stated, we plan to incorporate exogenous factors that encompass the four fundamental domains: economics, politics, climate, and health. Within these domains lie thousands of sub-categories on CEIC database. Consequently, selecting the appropriate subcategories demanded careful consideration to ensure relevance and accuracy in our analysis.

Our process for collecting data on exogenous variables is as follows: (1) We started with pinpointing the domain categories of interest, as previously delineated. A distinct database was established for each category, providing us with the ability to perform selections and modifications before finalizing the dataset. During this step, we collected data on more than 2,000 subcategories. (2) We organized the amassed databases into a uniform format, transformed them into a monthly data sequence, and ensured they span a consistent timeframe from January 2011 through March 2023. (3) We pinpointed ten critical exogenous variables in line with the given categories of our target forecasting data set. Our selection was guided by prior research insights, the data's completeness, and intuition. For example, we infer a direct correlation between the newborn birth rate and the consumer demand for maternal and baby care categories in FMCG industry. (4) Before fitting the data into the model, it's crucial to examine it thoroughly to ensure cleanliness and validity. We used the same methodology for exogenous variables as we did for the history sales dataset. Table 2-3 shows the exogenous variables we selected for our study. We group them into four categories and list the selection criteria in Table 3-3.

Table 3-3

List of exogenous variables in our study

#	Category	Exogenous Variable	Unit	Note
1	**Economy**	GDP (Gross Domestic Product)	USD MM	The expanding economy leading to increased consumer spending (Kira, 2013)
2		CPI (Consumer Price Index)	2012=100	
3		Exchange Rate (USD/INR)	USD	
4		Bombay Stock Exchange (FMCG)	1999=1000	
5		Wholesale Price Index	2011=100	
6	**Health**	Population	Person MM	Larger populations tend to drive greater demand for consumables (Ketkar & Ketkar, 1987)
7	**Climate**	Temperature India	Celsius	Climate change will have indirect impact on our economy and financial system, thus indirectly impact the consumer demand (Ciccarelli & Fulvia, 2024)
8		Humidity India	Percentage	
9	**Political**	Trade Balance	USD MM	Political actors affect firm performance in developed and emerging economies (Zheng, Singh, & Mitchell, 2015)
10		Political Stability and Absence of Violence	n/a	

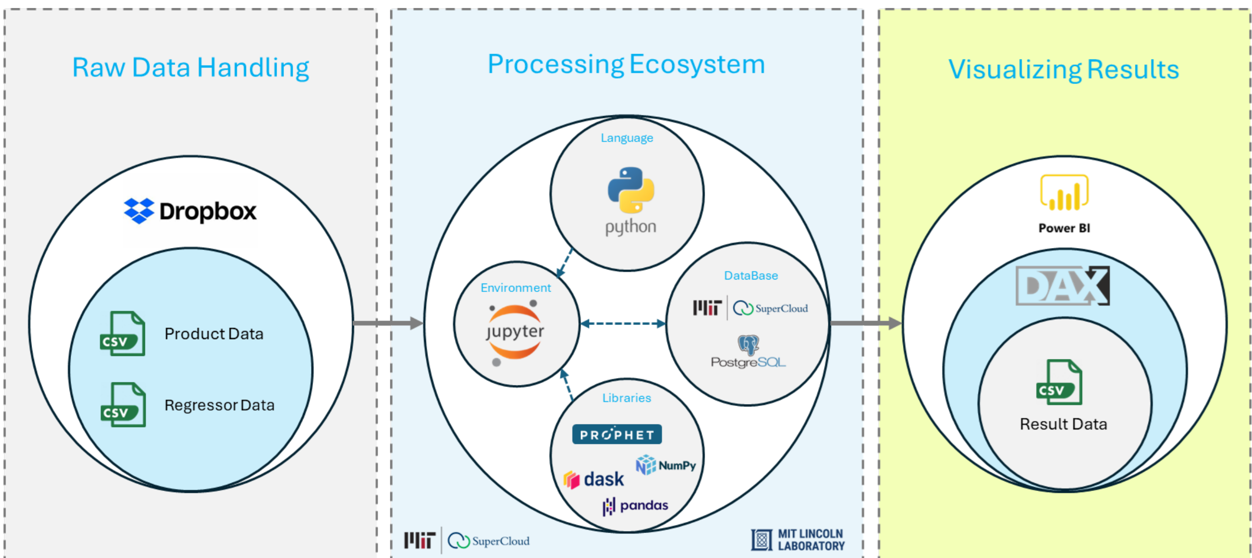
3.2. Forecasting Framework

3.2.1. Data Processing Ecosystem

After an initial evaluation, processing with local hardware (laptops/desktops) was deemed infeasible, as preliminary profiling pointed towards two to three months of consistent computing time to complete the 2.6 million iterations required for the project. A cloud-based architecture that enabled collaboration while utilizing superior computational power was set up, as seen in Figure 3-1. We opted to implement the MIT Lincoln Lab SuperCloud (LLSC) to support our computations due to the substantial computing requirements of our study. The LLSC plays a vital role in the implementation stage. It combines traditional HPC resources with modern tools for AI and Big Data research and provides interactive, on-demand high-performance computing to accelerate AI and ML research (Gadepally, Milechin, & Kepner, 2023). In this processing ecosystem, we used Python as our programming language; we introduced Prophet predictive library and Dropbox for retrieving files. We chose Colab as our processing environment for simple tasks and LLSC for processing demanding tasks.

Figure 3-1

Processing Ecosystem



3.2.2. Performance Evaluation

Machine learning algorithms learn from the data provided in a dataset, that is, the model is "trained" using this data. To assess how well the model performs, the data is typically split into two sets: one for training and another for testing. The test data which has "unseen" data points, are used to assess the progress and effectiveness of the algorithm's training. This process of training, testing, and validating is called Cross-Validation.

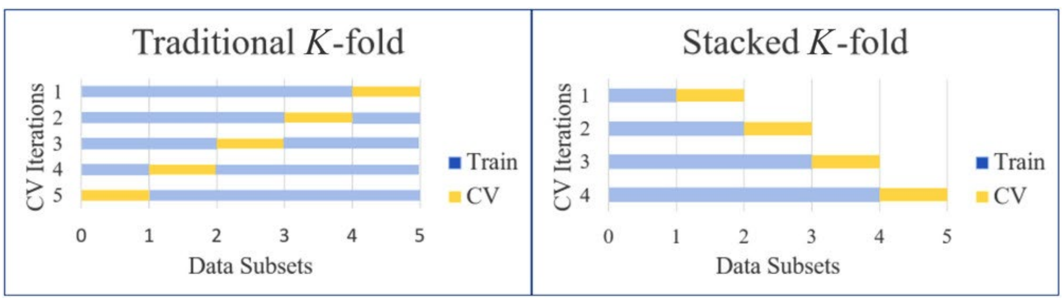
The Prophet model uses Simulated Historical Forecasts (SHFs) by producing K-forecasts at various cutoff points in history, chosen such that the horizons lie within history and the total error can be evaluated (Taylor & Letham, 2017).

As seen in Figure 3-1

Traditional VS Stacked K-Fold Cross Validation (Wang, Ram, Ramesh, & Joseph, 2022), the dataset in traditional cross-validation is randomly divided into “K” equally sized folds, however stacked K-fold (SHF) maintains the data sequence and uses only the time ordered data from previous iterations for training and validation. This process cycles through the dataset K times, maintaining a fixed size for the validation set while progressively expanding the training set as it moves through the original dataset (Wang, Ram, Ramesh, & Joseph, 2022). Starting from the first fold, the initial training data is called the “Initial” and for this project we used 24 months (about 2 years). The testing data is known as the “Horizon” and for this project we used 1 month.

Figure 3-1

Traditional VS Stacked K-Fold Cross Validation (Wang, Ram, Ramesh, & Joseph, 2022)



In setting the value of k for our cross-validation, we begin by designating an “Initial” training window of 24 months (from Jan 1, 2011 to Dec 1, 2013), with the subsequent month, known as the “Horizon” (Jan 1, 2014) serving as the test set. For the second iteration, the model expands the training set forward by one month, now using the first 25 months (from Jan 1, 2011, to Jan 1, 2014) for training while maintaining a single-month test range (Feb 1, 2014). This process continues, shifting the training window by one month each, while always testing the following month. By iterating this procedure, we end up with 116-119 separate cross-validation iterations, which corresponds to our k value for the stacked K-fold process.

To assess and compare forecasting errors across various configurations, we need to quantify these errors. By integrating insights from previous literature reviews and considering the structure of our data, we selected MAPE (Mean Absolute Percentage Error) as our forecasting error metric. The equation demonstrates how to calculate the MAPE error.

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left(\frac{y_t - \widehat{y_t}}{y_t}\right), \tag{2}$$

Where y_t is the actual demand on Month t and $\widehat{y_t}$ is the forecasted demand on Month t

In our study, we will employ $\Delta MAPE$ as a metric to assess the performance of the model under different configurations. This will determine whether the specific configuration enhances the model's forecasting accuracy, indicated by a decrease in MAPE, or diminishes it, evidenced by an increase in MAPE. The formula below illustrates how we calculate $\Delta MAPE$.

$$\Delta MAPE = MAPE - MAPE_{Baseline}, \tag{3}$$

Where $MAPE$ is the Mean Average Percent Error and $MAPE_{Baseline}$ is MAPE without regressor

3.3. Implementation

A systematic approach to data processing is crucial for achieving accurate predictions and efficiently utilizing computational resources. This section details general model sequences, the structure and computational methods employed.

3.3.1. Sequences, Structure and Setup

To answer the project research questions, 7 sequences were defined and a model template of 197 lines of Python code were executed as needed. These sequences ultimately tested exogenous factor (regressor) lags, adding/removing holidays and hyper-parameter combinations to determine the most impactful combinations. See Table A1 in Appendix A for a summary of sequence setups. Utilizing the Python (Anaconda 3.9) environment through a Jupyter Notebook framework, libraries including Pandas, Nympy and Prophet were loaded as a base for the script. The logic then merged product (SKU) and regressor data frames with the ‘Date’ column as the index. The target and feature columns were re-named to 'ds' and 'y' respectively and embedded into the required nested loop sequence. In total, 8 consecutive nested loops were embedded into 7 sequences in such a way it would iterate through, cross-validate, capture, and export all defined options.

3.3.2. Hyperparameters

Prophet utilizes 15 hyperparameters to control its learning process, 5 of which are preferred for tuning and 10 that are likely not needed to be tuned (META - Core Data Science Team, 2017). In its native state, Prophet defaults to set hyperparameters unless explicitly noted. Table 3-4 shows the Prophet default and calibrated hyperparameter map.

Table 3-4

Prophet Default and Calibrated Hyperparameter Map

<table>
<tr><th rowspan="2">Hyperparameter</th><th colspan="2">Default</th><th colspan="2">Calibration</th><th rowspan="2">Comment</th></tr>
<tr><th>Model Sequence</th><th>Value</th><th>Model Sequence</th><th>Values</th></tr>
<tr><td>growth</td><td rowspan="4">1,2,3,4,5,6</td><td>linear</td><td rowspan="4">7</td><td>linear, logistic</td><td>for logistic, saturation = max[y]</td></tr>
<tr><td>seasonality_mode</td><td>additive</td><td>additive, multiplicative</td><td></td></tr>
<tr><td>changepoint_prior_scale</td><td>0.05</td><td>0.05, 0.01, 0.10, 0.25, 0.50</td><td>effectively a lasso penalty</td></tr>
<tr><td>seasonality_prior_scale</td><td>10</td><td>1.0, 5.0, 10.0</td><td>effectively a ridge penalty</td></tr>
</table>

3.3.3. Processing Time, Parallelization and Clustering

The processing time for the run sequence largely depended on the model complexity. In its native state, Prophet runs its Cross-Validation in series, but can parallelize using processes such as threads and processes. The script was embedded with an ability to use both native parallelization within the Prophet model or SLURM Scheduling within the LLSC. For sequences 1 through 6, processing was initially attempted without parallelization but timed out after 12 hours in Google Colab. Initiating threading reduced this time to around 3 to 4 hours but using the LLSC and native parallelization (either threads or processes) reduced this time to 1.25hrs, a 90% reduction in processing time.

For sequence 7, however, the hyperparameter calibration options upped the iteration count by a factor of x60, so the current model setup was inadequate and needed a more advanced form of parallelization to execute the sequence. The solution was found by utilizing the “Dask” SLURM Client to scale clusters across the LLSC’s multiple nodes, cores and processes while disabling the model’s native parallelization. The reason for disabling parallelization in the model was to prevent model failure as daemonic processes are not allowed to have children. The average processing time for this final sequence clocked in at 9.375 hours.

In summary, we outlined a systematic data processing approach with seven model sequences to address research questions. Key highlights included the importance of parallelization, reducing processing time, and utilizing the Prophet model for efficient forecasting. The chapter emphasized leveraging threads, SLURM scheduling, and tuning hyperparameters to optimize performance for complex sequences.

4. RESULTS

To analyze the impact of exogenous variables on the forecasting accuracy of Prophet, we focus on pairing products (SKUs) with individual exogenous features in varying model configurations (refer to Appendix A for configurations details) and compare the prediction performance against a baseline. In total, 1.16 GB of data across 62 million datapoints were captured and consolidated for this analysis. Recall that we are working towards (1) identifying key exogenous variables relevant to FMCG demand forecasting, (2) assessing how different configurations of the AI/ML algorithm “Prophet” are affected by these exogenous variables and impact the model's overall accuracy and (3) developing strategies and recommendations for businesses better to integrate exogenous variables into their Prophet forecasting model. Snapshots of the Power BI Visualization Dashboard used to aid the analysis can be seen in Appendix C.

4.1. Baseline

Sequence 2 with no regressor was selected as baseline for the study for the following reasons: 1) data selected for exogenous variables are typically available from agencies with a 1 to 3-month lag period, 2) it is assumed that analysts would prefer to use “Default” hyperparameters as setup would require little time, 3) hyperparameter calibration requires some understanding of the model, product (SKU) and market and 4) it is a computationally intensive process which not all organizations may have access to the necessary power from High Performance Computing (HPC) centers, Distributed Computer Networks (DCN), etc.

4.2. Key Exogenous Variables

Table 4-1 shows the change in MAPE (ΔMAPE) for the Prophet model using sequence 2 (default hypermeters & 30-day regressor lag) with and without the exogenous features applied. The table aggregates all products (SKUs) using statistically normalized units as originally shared and uses the case of “No Regressor” (no exogenous factor) as the baseline case.

Table 4-1

Overall Impact (ΔMAPE) of adding Exogenous Features to Model.

Regressor Family		Regressor		
Name	Δ MAPE	Name	MAPE	Δ MAPE
Climate	0.63%	Humidity Monthly Median (%)	46.00%	**0.61%**
		Temperature India: Monthly Median (Celsius)	46.04%	**0.64%**
Economy	-1.16%	Bombay Stock Exchange: Index: Fast Moving Consumer Goods	42.05%	**-3.34%**
		Consumer Price Index (2012=100)	43.79%	**-1.61%**
		Gross Domestic Product (USD Mn)	45.09%	**-0.30%**
		Wholesale Price Index (WPI) (2011-2012=100)	46.02%	**0.62%**
Political	0.13%	Foreign Exchange Rate: RBI: Monthly Average: US Dollars (USD/INR)	44.94%	**-0.45%**
		Political Stability and Absence of Violence Terrorism Estimate	46.66%	**1.27%**
		Trade Balance (USD Mn)	44.97%	**-0.42%**
Population	-0.68%	Population Mn India (Person Mn)	44.72%	**-0.68%**
		*No Regressor**	45.40%	0.00%
		Mean	45.06%	**-0.33%**
Excluding Baseline		**Mean**	45.03%	**-0.37%**
		Min	42.05%	**-3.34%**
		Max	46.66%	**+1.27%**
		Range Half	±2.305%	**±2.305%**
		STDEV (σ)	**0.01**	
		CV	**0.03**	

**** Used as baseline.***

The first notable observation is the high average MAPE: $\overline{MAPE} = 45.06\%$, where the underlying reason lies within the limitations of this performance metric. Although all zeros in the original demand data (‘y’) were cleaned and imputed, 9 of the 5,184 datapoints are close to zero. These near zeros occurred during the 2020 year of data, and across all products (SKUs) in the “Skin” family and one product (SKU) in the “Personal” product family. Including these 9 points inflates the overall MAPE by +15.56%, however negating returns a $\overline{MAPE} = 29.84\%$. See Appendix B Table – B1 for a summary table, similar to Table 4–1, of the performance summary negating these near zero points. Narrowing in on the impact of added exogenous features, we looked at the change in MAPE: $\overline{\Delta MAPE} = -0.37\%$. The delta indicates there is an overall impact, and the range further indicates that exogenous feature selection is of particular importance and can either positively or negatively affect the model's performance. We see that 6 of the 10 features help improve the MAPE, and the 4 balance worsens it. Of these, the economic family had the best overall impact with a MAPE delta of -1.16%, with the feature "Bombay Stock Exchange: Index: Fast Moving Consumer Goods" having the best improvement on MAPE, at -3.34%. The Climate family had the worst overall impact on MAPE at a delta of +0.63%. The Political family had one feature "Political Stability and Absence of Violence Terrorism Estimate" with an overall impact of +1.27%, however the other 2 features in the family showed to have a NET benefit.

Figure 4-1

ΔMAPE Visualization by Regressor Family

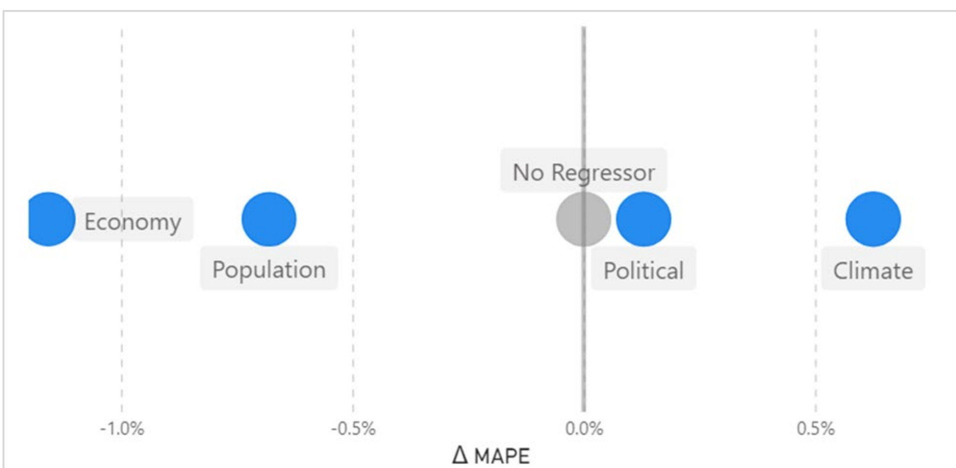


Figure 4-1 visualizes an aggregated view of impact by family, where the four blue circles represent the groups of exogenous variables, and the grey circle represents the baseline. The figure highlights Population and Economy families reducing the MAPE value and the Political and Climate families increasing the MAPE value. The impact of each exogenous factor also varies depending on the product (SKU) it is applied to.

Figure 4-2 helps visualize this by displaying an example using the economic feature "Bombay Stock Exchange: Index: Fast Moving Consumer Goods" as applied to various product families. We see that families: 1) Skin, 2) Oral, 3) Air, 4) Hair, 5) Fabric and 6) Personal all have improved MAPE's when this exogenous feature is applied as a regressor. Comparatively, families 7) Blades & Razors, 8) Health, 9) Baby and 10) Female were impacted in the opposite fashion, observing a NET increase in ΔMAPE when applied. Looking at the "Skin" product family, we see that it acts almost as an outlier, showing a remarkable improvement in MAPE with a delta (Δ) of -18.12%. The underlying reason for this revolves around the 9 dates mentioned earlier, whereby the application of the exogenous feature acted as a "buffer". It should be noted however that the MAPE of the Skin family even after the feature was applied, was still very high at 118.38%, indicating that although MAPE improvement was observed, there was still room for improvement to the model, which was further confirmed when looking at the families R^2 of 0.37.

Figure 4-2

ΔMAPE Visualization by Product Family for "Bombay Stock Exchange: Index: Fast Moving Consumer Goods"

Overall, although exogenous variables built into the default model can help to reduce the MAPE, there is still a chance of notable underfit using this configuration. If we are to have a usable model, further steps are needed to better fit historical data. A summary of the impact of each exogenous feature family on individual products (SKUs) is captured in Appendix B Table B-2.

4.3. Assessment of Different Configurations

There were three approaches to better fit the model, these being:

Configuration 1 - Varying the Regressor Lag from 0 to 90 days.

Configuration 2 - Excluding Regional Holidays or the Covid shutdown from the training data.

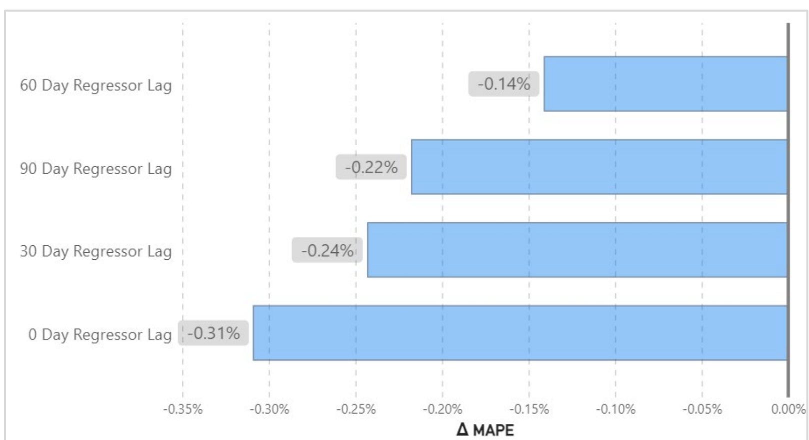
Configuration 3 – Hyperparameter calibration (tuning).

4.3.1. Configuration 1 - Varying Regressor Lags

As seen in Figure 4-3, varying values of regressor lag were investigated. Specifically, they were 0 days, 30 days, 60 days and 90 days. It was observed that the less regressor lag applied to the model, the better the impact (larger negative ΔMAPE) on the model. However, as noted in Section 4.1, although zero regressor lag is preferred, it is not practical as the availability of exogenous data, especially economic, political and population data typically lagged between 30 to 90 days. In addition to that, the impact on the model is also minimal with $\overline{\Delta MAPE} = -0.23\%$.

Figure 4-3

$\Delta MAPE$ for varying Regressor Lag Values of Applied Exogenous Variables

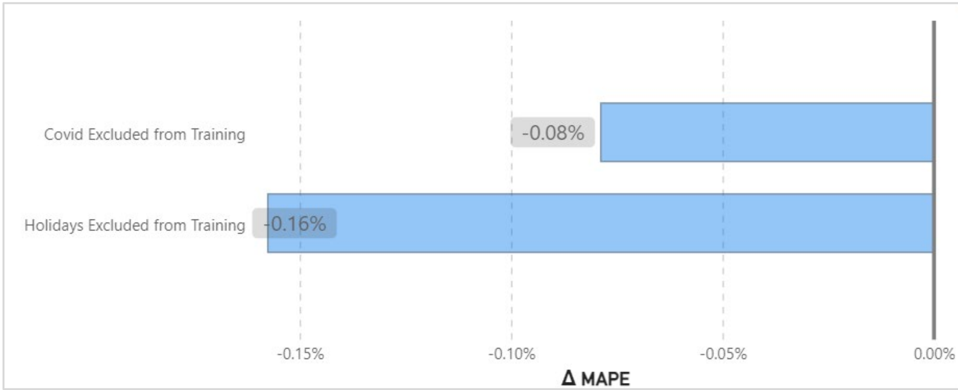


4.3.2. Configuration 2 - Impact of Excluding Holidays

As with the regressor lag, the impact of excluding holidays or the Covid shutdown days from the models training dataset had negligible impact. Figure 4-4 details the results, showing an $\Delta MAPE$ of -0.16% and -0.08% respectively.

Figure 4-4

$\Delta MAPE$ for Excluding Regional Holidays or the Covid Shutdown from the Training Data



4.3.3. Configuration 3 - Hyperparameter Calibration (Tuning)

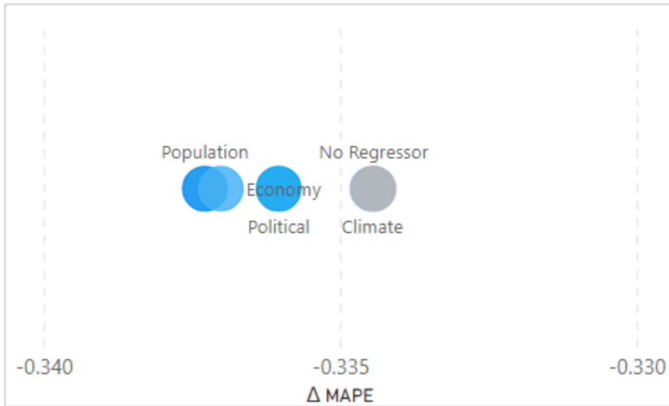
The Prophet data science team recommended 5 key hyperparameters to focus on calibrating (META - Core Data Science Team, 2017), these are 1) growth, 2) seasonality_mode, 3) changepoint_prior_scale, 4) seasonality_prior_scale and 5) holidays_prior_scale, however since the impact of holidays was already analyzed in section 4.4.2., holidays_prior_scale was not included in the calibration set as to save on computational time. This final approach consisted of a 60 hyperparameter option grid, of which details can be found in Table 3-4

Appendix B Table – B4 summarizes a count of the best parameters used to obtain the best fit.

There was an astounding impact on reducing the MAPE with or without regressors built in. Grouping by regressor families, we see $\overline{\Delta MAPE} = -33.30\%$, as compared to the baseline noted in Section 4.1. Only the Climate Family hoovered around having little effect as compared to no regressor (see Figure 4-5).

Figure 4-5

$\Delta MAPE$ on Regressor Family after Calibrating Model



Grouping by product (SKU) (Figure 4-6) reveal even more significant observations, such as 1) that every product (SKU) now has a positive impact when both calibration and exogenous variables were built into the model, 2) the R^2 is trending in the right direction for all products (SKUs), with an $\overline{R^2} = 0.51 \pm 0.44$ as compared to previously where $\overline{R^2} = 0.35 \pm 0.50$, and 3) as the ΔMAPE gets larger (see the case of Oral and Baby), the model fit (R^2) also improves. Although there is a notable increase in model fit, additional hyperparameters and combinations can be added to the iteration sequence to obtain an even better fit.

Figure 4-6

$\Delta MAPE$ on Product Family after Calibrating Model. NOTE Skin Family removed as results were off the chart.

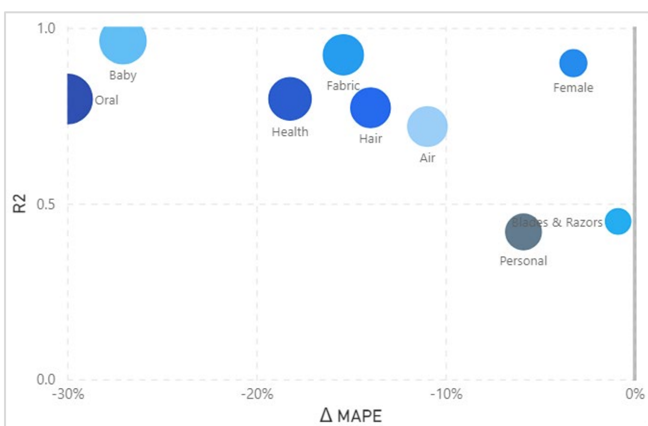


Table 4-2 uses the standard category for forecasting evaluation (refer to Meade, 1983, Table 3-5) to summarize and better understand the overall impact calibration had on selecting the appropriate hyperparameters. What we see is that before calibration, 44.4% of products (SKUs) had a model with a "Very good" or "Good" fit, however after calibration, this number almost doubled to 80.5%, indicating that calibration is essential for adequate modeling.

Table 4-2

Model Accuracy Before and After Calibration

Model Forecast Accuracy	MAPE		Product (SKU) Count			
	Lower (>)	Upper (<=)	Before Calibration		After Calibration	
	%	%	#	%	#	%
Very Good	0	10	3	8.3%	8	22.2%
Good	10	20	13	36.1%	21	58.3%
Good Enough	20	50	15	41.7%	6	16.7%
Not good	50	∞	5	13.9%	1	2.8%

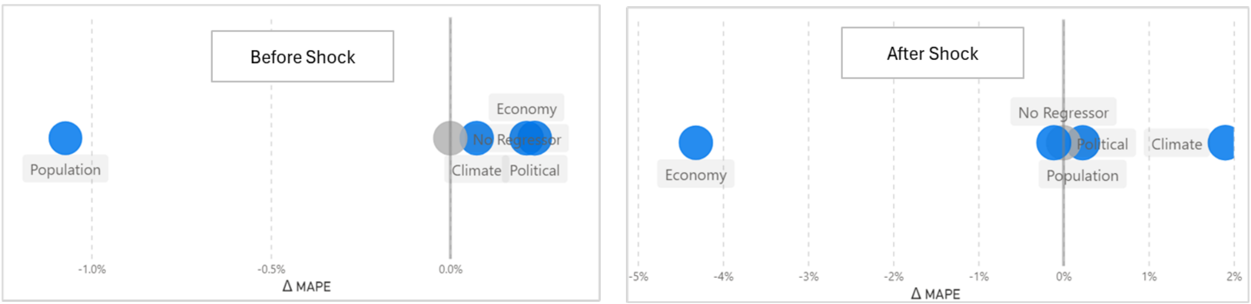
4.4. Impact of Disruption

We also analyzed the impact of exogenous variables before 2020 (Covid-19) and after. It was found that before, the model was negligibly impacted by the added exogenous features, showing a $\overline{\Delta MAPE} = -0.06\%$, and a $\overline{MAPE} = 23.38\%$. However, after 2020, exogenous features showed to have a $\overline{\Delta MAPE} = -1.24\%$, a significant jump, but a concern was the models' response to shock as the accuracy even with exogenous variables added spiked $\overline{MAPE} = 92.22\%$. This indicates the model did not handle disruption well using default parameters, though, the added regressors did help in buffering some of the impact from shock.

Looking at exogenous feature outliers in the before and after periods (see Figure 4-7) are the population and economy families. It was observed that before 2020, population-based exogenous variables were dominant, but after 2020, economy was the most impactful family. The nature of the raw data coming from the Indian Sub-Continent (an emerging market) could help us conclude that it is important to understand the drivers of the product (SKU) in addition to geopolitical landscapes as to properly target applicable exogenous features.

Figure 4-7

$\Delta MAPE$ Before and After Covid-19



4.5. Practical Recommendation

It is evident that although ML models are advancing and supporting businesses with modeling, particular attention should be paid to analyst competency with "analyst-in-the-loop" models (such as Prophet), as domain and model expertise remain central to ensuring accurate forecasting and model performance. A good understanding of the product's (SKU) value chain and leavers driving the product's (SKUs) positioning in its growth cycle is also necessary before selecting regressors to build into models. It is important to understand the products (SKUs) susceptibility to geopolitics as these variables have the potential to trump exogenous features historically accepted as a "good fit".

5. CONCLUSION

In our study, the research question "*How can exogenous variables improve AI/ML forecasting in the Fast-Moving Consumer Goods (FMCG) industry?*" has been explored and summarized as follows:

1) In general, exogenous variables have a NET benefit that improves the forecasting performance of the Prophet model in the Fast-Moving Consumer Goods (FMCG) industry. The overall ΔMAPE improvement was **-0.37%** with an exogenous variable built into the default model, and **-16.62%** with the inclusion of a targeted exogenous variable combined with hyperparameter calibration.
2) The key exogenous variables relevant to demand forecasting of Fast-Moving Consumer Goods (FMCG) using the Prophet model were the Economic and Population Families of variables. The "Bombay Stock Exchange: Index: Fast Moving Consumer Goods" was the most impactful, with an overall ΔMAPE improvement of **-3.34%.**
3) Tables in Appendix B further detail summarized insight that can aid analysts and practitioners with unique configuration strategies for integrating these exogenous variables into FMCG demand forecasting using the Prophet model.

REFERENCES

Abolghasemi, M., Beh, E., Tarr, G., & Gerlach, R. (2020). Demand forecasting in supply chain: The impact of demand volatility in the presence of promotion. *Computers & Industrial Engineering, 142*, 1.

Aichner, T., & Santa, V. (2023). Demand Forecasting Methods and the Potential of Machine Learning in the FMCG Retail Industry. In T. Aichner, *Serving the Customer: The Role of Selling and Sales* (pp. 215-252). Springer, Wiesbaden.

Akkermans, H., Bogerd, P., Yücesan, E., & Wassenhove, L. (2003). The impact of ERP on supply chain management: Exploratory findings from a European Delphi study. *European Journal of Operational Research*, 284-301.

Amar, J., Rahimi, S., Surak, Z., & Bismarck, N. (2022). *AI-driven operations forecasting in data-light environments*. Retrieved from Mckinsey & Company: https://www.mckinsey.com/capabilities/operations/our-insights/ai-driven-operations-forecasting-in-data-light-environments

Argandoña, A. (2017). Gross Domestic Product (GDP) and Gross National Product (GNP). *Encyclopedia of Business Ethics and Society, Forthcoming, IESE Business School Working Paper No. 1153-E*.

Carbonneau, R., Laframboise, K., & Vahidov, R. (2008). pplication of machine learning techniques for supply chain demand forecasting. *European Journal of Operational Research, 184*(3), 1140-1154.

CEIC. (2023). *CEIC*. Retrieved from https://www.ceicdata.com/en/about-us

Cerqueira, V., Torgo, L., & Soares, C. (2019). *Machine Learning vs Statistical Methods for Time Series Forecasting: Size Matters.* arXiv preprint arXiv:1909.13316 .

Chui , M., Henke, N., & Miremadi, M. (2019). *Most of AI's business uses will be in two areas*. Retrieved from QuantumBlack AI by Mckinsey: https://www.mckinsey.com/capabilities/quantumblack/our-insights/most-of-ais-business-uses-will-be-in-two-areas

Ciccarelli, M., & Fulvia, M. (2024). Demand or supply? An empirical exploration of the effects of climate change on the macroeconomy. *Energy Economics, 129*(2024).

Feizabadi, J. (2022). Machine learning demand forecasting and supply chain performance. *International Journal of Logistics Research and Applications, 25*(2), 1.

Gadepally, V., Milechin, L., & Kepner, J. (2023). *MIT SuperCloud for AI Algorithm Development.* Retrieved from https://www.mit.edu/~kepner/QuestLaunch/QuestLaunch-MIT-SuperCloud.pdf

GitHub. (2023). *GitHub*. Retrieved from Prophet: https://facebook.github.io/prophet/

Graf, B. (2020). *Consumer Price Index Manual.* International Monetary Fund.

Hastie, T., & Tibshirani, R. (1987). Generalized additive models: some applications. *Journal of the American Statistical Association, 82*(398), 371-386.

Hyndman, R. (2006). Another look at forecast-accuracy metrics for intermittent demand. *Foresight: The International Journal of Applied Forecasting, 4*(4), 43-46.

Hyndman, R., & George, A. (2018). *Forecasting: principles and practice.* OTexts.

Hyndman, R., Athanasopoulos, G., Bergmeir, C., Caceres, G., Chhay, L., O'Hara-Wild, M., . . . Yasmeen, F. (2018). *forecast: Forecasting functions for time series and linear models.*

Jackson, I., & Ivanov, D. (2023). A beautiful shock? Exploring the impact of pandemic shocks on the accuracy of AI forecasting in the beauty care industry. *Transportation Research Part E: Logistics and Transportation Review, 180*.

Ketkar, K., & Ketkar, S. (1987). Population dynamics and consumer demand. *Applied Economics*, 1483-1495.

Kira, A. R. (2013). The Factors Affecting Gross Domestic Product (GDP) in Developing Countries: The Case of Tanzania. *European Journal of Business and Management*.

Kolassa, S., & Siemsen, E. (2016). *Demand Forecasting for Managers.* New York: Business Expert Press, LLC.

Leonard, k. (2018). *Factors That May Be Endogenous and Exogenous in a Business*. Retrieved from Chron: https://smallbusiness.chron.com/operating-leverage-business-risk-71952.html

Litvak, O. (2020). *Demand Forecasting: Factors Affecting It, Why It is Important, & More*. Retrieved from mize: https://mize.tech/blog/demand-forecasting-factors-affecting-it-why-it-is-important-more/

Meade, N. (1983). Industrial and business forecasting methods, Lewis, C.D., Borough Green, Sevenoaks, Kent: Butterworth, 1982. Price: £9.25. Pages: 144. *Journal of Forecasting, 2*(3).

META - Core Data Science Team. (2017). *Diagnostics*. Retrieved from Prophet | Forecasting at Scale: https://facebook.github.io/prophet/docs/diagnostics.html

Nasseri, M., Falatouri, T., Brandtner, P., & Darbanian, F. (2023). Applying Machine Learning in Retail Demand Prediction—A Comparison of Tree-Based Ensembles and Long Short-Term Memory-Based Deep Learning. *Applied Sciences, 13*(19).

Peters, A. H. (1990). Estimation procedures for structural time series models. *Journal of Forecasting*, 89-108.

Pontoh, R., Zahroh, S., Nurahman, H., Aprillion, R., Ramdani, A., & Akmal, D. (2021). Applied of feed-forward neural network and facebook prophet model for train passengers forecasting. *J. Phys.: Conf. Ser., 1776*.

Renold, M., Vollenweider, J., Mijovic, N., Kuljanin, J., & Kalic, M. (2023). Methodological framework for a deeper understanding of airline profit cycles in the context of disruptive exogenous impacts. *Journal of Air Transport Management, 106*.

Revilla, E., & Sáenz, M. J. (2013). Supply chain disruption management: Global convergence vs national specificity. *Journal of Business Research, 67*(2014).

Revilla, E., Sáenz, M. J., Seifert, M., & Ma, Y. (2023). Human–Artificial Intelligence Collaboration in Prediction: A Field Experiment in the Retail Industry. *Journal of Management Information Systems, 40*(4), 1071-1098.

Rizzi, A. (2022). *Supply Chain Fundamentals and Best Practices to Compete by Leveraging the Network.* Springer Cham.

Sinaga, O., Saudi, M., & Roespinoedji, D. (2018). The relationship between economic indicators, gross domestic product (GDP) and supply chain performance. *Polish Journal of Management Studies, 18*(1), 338-352.

Sivaramakrishnan, S., Fernandez, T. F., Babukarthik, R., & Premalatha, S. (2021). Forecasting Time Series Data Using ARIMA and Facebook Prophet Models. In *Big data management in Sensing* (pp. 47-59). River Publishers.

Snyder, L., & Shen, Z.-J. M. (2019). *Fundamentals of supply chain theory.* John Wiley & Sons.

Sornette, D., Deschâtres, F., Gilbert, T., & Ageon, Y. (2004). Endogenous Versus Exogenous Shocks in Complex Networks: An Empirical Test Using Book Sale Rankings. *Physical Review Letters, 93*(22).

Spyros, M., Wheelwright, S., & Hyndman, R. (1998). *Forecasting methods and applications.* John wiley & sons.

Syam, N., & Sharma, A. (2018). aiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. *Industrial Marketing Management, 69*, 135-146.

Syntetos, A. A., Babai, Z., Boylan, J. E., Kolassa, S., & Nikolopoulos, K. (2016). Supply chain forecasting: Theory, practice, their gap and the future. *European Journal of Operational Research, 252*(1), 1-26.

Taylor, S., & Letham, B. (2017). Forecasting at scale. *PeerJ Preprints*.

Tianyu , F., Zheng, Z., Jiaying, X., Minghui , L., Ming , L., Huanhuan, J., & Xihe, Y. (2022). The comparative analysis of SARIMA, Facebook Prophet, and LSTM for road traffic injury prediction in Northeast China. *Frontiers in public health, 10*.

van Donselaar, K., Vishal, G., van Woensel, T., Broekmeulen, R., & Fransoo, J. (2010). Ordering Behavior in Retail Stores and Implications for Automated Replenishment. *Management Science, 56*(5), 766-784.

Wang, L., Ram, G., Ramesh, S., & Joseph, P. (2022). Forecasting venue popularity on location-based services using interpretable machine learning. *Production and Operations Management, 31*(7), 2773-2788.

Yasir , M., Ansari, Y., Latif, K., Maqsood, H., Habib, A., Moon, J., & Rho, S. (2022). Machine learning–assisted efficient demand forecasting using endogenous and exogenous indicators for the textile industry. *International Journal of Logistics Research and Applications*, 1-20.

Zheng, W., Singh, K., & Mitchell, W. (2015). Buffering and enabling: The impact of interlocking political ties on firm survival and sales growth. *Strategic Management Journal, 36*(11).

APPENDIX A – SEQUENCE DETAILS

Table A1

Summary of Prophet Model Sequences

Sequence	Addresses Which Research Question?	Initial (Day)	Horizon (Day)	Period (Day)	Regressor Lag (Day)	Holidays Included?	Hyper-Parameter Selection	Parallelization	Computation Time (Hr)
1	1, 2	730	30	30	0	Yes	Default	Native Threads	1.25
2	1, 2, 3	730	30	30	30	Yes	Default	Native Threads	1.25
3	1, 2	730	30	30	60	Yes	Default	Native Threads	1.25
4	1, 2	730	30	30	90	Yes	Default	Native Threads	1.25
5	1, 2	730	30	30	30	No	Default	Native Threads	1.25
6	1, 2	730	30	30	30	Covid Excl.	Default	Native Threads	1.25
7	3	730	30	30	30	Yes	Calibrated	LLSC - Dask SLURM	9.375

APPENDIX B – ANALYSIS DETAILS

Table – B1

Summary table of the impact of Regressors negating 9 near to zero datapoints.

Regressor Family		Regressor		
Name	**Δ MAPE**	**Name**	**MAPE**	**Δ MAPE**
Climate	-0.20%	Humidity Monthly Median (%)	30.12%	-0.20%
		Temperature India: Monthly Median (Celsius)	30.14%	-0.21%
Economy	0.26%	Bombay Stock Exchange: Index: Fast Moving Consumer Goods	28.98%	0.94%
		Consumer Price Index (2012=100)	28.94%	0.99%
		Gross Domestic Product (USD Mn)	30.29%	-0.37%
		Wholesale Price Index (WPI) (2011-2012=100)	30.46%	-0.54%
Political	-0.13%	Foreign Exchange Rate: RBI: Monthly Average: US Dollars (USD/INR)	29.70%	0.22%
		Political Stability and Absence of Violence Terrorism Estimate	30.47%	-0.54%
		Trade Balance (USD Mn)	30.01%	-0.08%
Population	0.71%	Population Mn India (Person Mn)	29.22%	0.71%
*No Regressor**			29.92%	0.00%
		Average	29.84%	0.08%
Excluding Baseline		**Average**	29.83%	+0.09%
		Min	28.94%	-0.54%
		Max	30.47%	+0.99%
		Range Half	±0.765%	±0.765%
		STDEV	0.01	
		CV	0.02	

Table – B2

Summary table of the impact of Regressors by Product (SKU)

Product	Climate Baseline*	Climate MAPE	Climate Δ MAPE	Climate R2	Economy Baseline*	Economy MAPE	Economy Δ MAPE	Economy R2
Air1	26.61%	26.89%	0.28%	0.40	26.61%	26.34%	-0.27%	0.47
Baby1	13.50%	13.82%	0.32%	-0.12	13.50%	13.05%	-0.45%	0.03
Baby2	141.45%	140.19%	-1.26%	0.69	141.45%	131.88%	-9.57%	0.74
Baby3	21.65%	22.12%	0.47%	0.80	21.65%	20.58%	-1.07%	0.86
BR1	9.86%	9.77%	-0.09%	0.39	9.86%	9.89%	0.03%	0.37
Fabric1	15.80%	15.88%	0.08%	-0.23	15.80%	15.57%	-0.23%	-0.13
Fabric3	22.23%	22.70%	0.47%	0.69	22.23%	22.17%	-0.06%	0.71
Fabric9	69.26%	71.79%	2.53%	0.76	69.26%	60.30%	-8.96%	0.78
Female1	9.89%	10.08%	0.19%	0.86	9.89%	9.76%	-0.13%	0.87
Female2	9.17%	9.38%	0.21%	-0.03	9.17%	9.52%	0.35%	-0.08
Female4	15.44%	15.46%	0.02%	0.81	15.44%	15.00%	-0.44%	0.81
Female6	10.46%	10.48%	0.02%	0.70	10.46%	10.51%	0.05%	0.70
Hair1	16.22%	16.23%	0.01%	0.50	16.22%	16.17%	-0.05%	0.53
Hair2	16.49%	16.62%	0.13%	0.11	16.49%	16.98%	0.49%	0.09
Hair3	17.97%	18.32%	0.35%	-0.29	17.97%	17.33%	-0.64%	-0.04
Hair4	40.57%	41.17%	0.60%	-0.37	40.57%	39.77%	-0.80%	-0.32
Hair5	49.52%	50.77%	1.25%	-0.10	49.52%	51.86%	2.34%	0.00
Health1	53.86%	54.16%	0.30%	0.16	53.86%	56.22%	2.36%	0.16
Health3	40.48%	41.04%	0.56%	0.68	40.48%	38.77%	-1.71%	0.69
Health4	16.15%	16.18%	0.03%	0.73	16.15%	16.22%	0.07%	0.73
Health6	19.47%	19.65%	0.18%	0.70	19.47%	19.87%	0.40%	0.69
Oral1	20.85%	21.20%	0.35%	-0.10	20.85%	20.70%	-0.15%	0.05
Oral2	124.80%	124.53%	-0.27%	0.17	124.80%	129.93%	5.13%	0.36
Oral4	17.26%	17.54%	0.28%	0.17	17.26%	17.59%	0.33%	0.18
Oral5	18.83%	19.01%	0.18%	0.67	18.83%	18.99%	0.16%	0.69
Oral6	27.84%	28.11%	0.27%	0.19	27.84%	28.28%	0.44%	0.22
Personal10	20.45%	20.75%	0.30%	-0.22	20.45%	20.40%	-0.05%	-0.03
Personal5	19.13%	19.28%	0.15%	0.27	19.13%	19.53%	0.40%	0.26
Personal6	25.75%	26.23%	0.48%	-0.02	25.75%	25.57%	-0.18%	0.03
Personal7	22.83%	22.86%	0.03%	0.18	22.83%	23.81%	0.98%	0.17
Personal9	18.78%	18.60%	-0.18%	0.13	18.78%	19.32%	0.54%	0.13
Skin1	354.19%	368.09%	13.90%	0.16	354.19%	313.26%	-40.93%	0.23
Skin2	128.61%	123.57%	-5.04%	0.13	128.61%	130.00%	1.39%	0.19
Skin3	83.13%	88.48%	5.35%	0.04	83.13%	86.44%	3.31%	0.06
Skin4	63.14%	63.78%	0.64%	0.30	63.14%	67.92%	4.78%	0.37
Skin5	52.68%	52.12%	-0.56%	0.15	52.68%	53.17%	0.49%	0.13
AVERAGE	45.40%	46.02%	0.63%	0.28	45.40%	44.24%	-1.16%	0.32

Product	Political Baseline*	Political MAPE	Political Δ MAPE	Political R2	Population Baseline*	Population MAPE	Population Δ MAPE	Population R2
Air1	26.61%	26.56%	-0.05%	0.49	26.61%	25.06%	-1.55%	0.47
Baby1	13.50%	13.47%	-0.03%	-0.15	13.50%	13.80%	0.30%	-0.18
Baby2	141.45%	139.01%	-2.44%	0.69	141.45%	130.94%	-10.51%	0.72
Baby3	21.65%	21.59%	-0.06%	0.82	21.65%	22.13%	0.48%	0.80
BR1	9.86%	10.21%	0.35%	0.36	9.86%	10.21%	0.35%	0.35
Fabric1	15.80%	16.04%	0.24%	-0.26	15.80%	15.89%	0.09%	-0.36
Fabric3	22.23%	22.53%	0.30%	0.71	22.23%	20.49%	-1.74%	0.76
Fabric9	69.26%	69.10%	-0.16%	0.77	69.26%	71.14%	1.88%	0.76
Female1	9.89%	10.02%	0.13%	0.87	9.89%	10.44%	0.55%	0.86
Female2	9.17%	9.42%	0.25%	-0.06	9.17%	9.54%	0.37%	-0.18
Female4	15.44%	15.60%	0.16%	0.81	15.44%	16.13%	0.69%	0.82
Female6	10.46%	10.37%	-0.09%	0.72	10.46%	10.04%	-0.42%	0.71
Hair1	16.22%	16.39%	0.17%	0.51	16.22%	16.40%	0.18%	0.52
Hair2	16.49%	16.97%	0.48%	0.10	16.49%	17.05%	0.56%	0.07
Hair3	17.97%	18.10%	0.13%	-0.24	17.97%	17.67%	-0.30%	-0.21
Hair4	40.57%	40.62%	0.05%	-0.26	40.57%	37.14%	-3.43%	0.00
Hair5	49.52%	53.23%	3.71%	-0.02	49.52%	44.16%	-5.36%	0.30
Health1	53.86%	54.27%	0.41%	0.17	53.86%	56.59%	2.73%	0.11
Health3	40.48%	39.49%	-0.99%	0.69	40.48%	38.13%	-2.35%	0.70
Health4	16.15%	16.05%	-0.10%	0.73	16.15%	16.09%	-0.06%	0.73
Health6	19.47%	19.33%	-0.14%	0.70	19.47%	19.30%	-0.17%	0.70
Oral1	20.85%	20.79%	-0.06%	0.06	20.85%	21.02%	0.17%	-0.05
Oral2	124.80%	123.49%	-1.31%	0.24	124.80%	119.04%	-5.76%	0.38
Oral4	17.26%	17.47%	0.21%	0.18	17.26%	17.37%	0.11%	0.21
Oral5	18.83%	18.88%	0.05%	0.68	18.83%	19.14%	0.31%	0.67
Oral6	27.84%	28.34%	0.50%	0.22	27.84%	29.26%	1.42%	0.19
Personal10	20.45%	20.43%	-0.02%	-0.16	20.45%	20.91%	0.46%	-0.22
Personal5	19.13%	19.43%	0.30%	0.23	19.13%	18.90%	-0.23%	0.28
Personal6	25.75%	25.83%	0.08%	0.02	25.75%	25.10%	-0.65%	0.04
Personal7	22.83%	23.50%	0.67%	0.14	22.83%	22.50%	-0.33%	0.19
Personal9	18.78%	19.02%	0.24%	0.14	18.78%	18.27%	-0.51%	0.13
Skin1	354.19%	350.50%	-3.69%	0.21	354.19%	353.54%	-0.65%	0.19
Skin2	128.61%	132.27%	3.66%	0.08	128.61%	128.44%	-0.17%	0.13
Skin3	83.13%	84.93%	1.80%	0.03	83.13%	84.03%	0.90%	0.05
Skin4	63.14%	62.87%	-0.27%	0.34	63.14%	63.12%	-0.02%	0.33
Skin5	52.68%	52.88%	0.20%	0.10	52.68%	50.83%	-1.85%	0.15
AVERAGE	45.40%	45.53%	0.13%	0.30	45.40%	44.72%	-0.68%	0.31

Product	Totals Baseline*	Totals MAPE	Totals Δ MAPE	Totals R2
Air1	26.61%	26.21%	-0.40%	0.46
Baby1	13.50%	13.54%	0.03%	-0.10
Baby2	141.45%	135.51%	-5.95%	0.71
Baby3	21.65%	21.61%	-0.04%	0.82
BR1	9.86%	10.02%	0.16%	0.37
Fabric1	15.80%	15.85%	0.05%	-0.25
Fabric3	22.23%	21.97%	-0.26%	0.72
Fabric9	69.26%	68.08%	-1.18%	0.77
Female1	9.89%	10.08%	0.19%	0.87
Female2	9.17%	9.47%	0.29%	-0.09
Female4	15.44%	15.55%	0.11%	0.81
Female6	10.46%	10.35%	-0.11%	0.71
Hair1	16.22%	16.30%	0.08%	0.51
Hair2	16.49%	16.91%	0.41%	0.09
Hair3	17.97%	17.86%	-0.11%	-0.19
Hair4	40.57%	39.68%	-0.90%	-0.24
Hair5	49.52%	50.01%	0.49%	0.04
Health1	53.86%	55.31%	1.45%	0.15
Health3	40.48%	39.36%	-1.12%	0.69
Health4	16.15%	16.14%	-0.02%	0.73
Health6	19.47%	19.54%	0.07%	0.70
Oral1	20.85%	20.93%	0.08%	-0.01
Oral2	124.80%	124.25%	-0.55%	0.29
Oral4	17.26%	17.49%	0.23%	0.18
Oral5	18.83%	19.01%	0.18%	0.68
Oral6	27.84%	28.50%	0.66%	0.20
Personal10	20.45%	20.62%	0.17%	-0.16
Personal5	19.13%	19.29%	0.16%	0.26
Personal6	25.75%	25.68%	-0.07%	0.02
Personal7	22.83%	23.17%	0.34%	0.17
Personal9	18.78%	18.80%	0.02%	0.13
Skin1	354.19%	346.35%	-7.84%	0.20
Skin2	128.61%	128.57%	-0.04%	0.13
Skin3	83.13%	85.97%	2.84%	0.04
Skin4	63.14%	64.42%	1.28%	0.33
Skin5	52.68%	52.25%	-0.43%	0.13
AVERAGE	45.40%	45.13%	-0.27%	0.30

Table – B3

Summary of best overall combination of Regressor and Hyperparameters per product (SKU)

Product	MAPE (Baseline)	MAPE	Δ MAPE	R2 (Baseline)	R2	Δ R2	Best Regressor Family	Best Regressor	Growth Mode	Change Point Priority Scale	Seasonality Mode	Seasonality Priority Scale	Note
Air1	29.56%	12.90%	-16.65%	0.49	0.72	0.23	Political	Trade Blance (USD mn)	linear*	0.25	additive*	10.0*	
Baby1	9.20%	6.33%	-2.87%	0.03	0.41	0.38	Economy	Wholesale Price Index (WPI) (2011-2012=100)	linear*	0.5*	additive*	10.0*	Covid Excluded from Training
Baby2	146.65%	14.38%	-132.27%	0.74	0.96	0.23	Economy	Bombay Stock Exchange: Index: Fast Moving Consumer Goods: Month Average (01Feb1999=1000)	linear*	0.5*	multiplicative	10.0*	
Baby3	19.01%	9.40%	-9.61%	0.86	0.95	0.09	No Regressor	None	linear*	0.25	multiplicative	0.1	
BR1	9.36%	7.93%	-1.43%	0.39	0.45	0.06	Climate	Temperature India: Monthly Median (Celsius)	linear*	0.25	additive*	0.1	
Fabric1	22.83%	16.13%	-6.70%	-0.13	0.08	0.21	Climate	Temperature India: Monthly Median (Celsius)	linear*	0.25	multiplicative	1.0	
Fabric3	16.97%	12.70%	-4.27%	0.76	0.78	0.02	Political	Trade Blance (USD mn)	logistic	0.5*	additive*	0.1	
Fabric9	66.35%	14.04%	-52.31%	0.78	0.92	0.14	Political	Trade Blance (USD mn)	linear*	0.5*	multiplicative	10.0*	
Female1	11.01%	7.29%	-3.72%	0.87	0.90	0.03	Political	Political Stability and Absence of ViolenceTerrorism Estimate	logistic	0.01	multiplicative	10.0*	
Female2	11.77%	6.90%	-4.87%	-0.03	0.09	0.12	Economy	Consumer Price Index (2012=100)	logistic	0.10	multiplicative	10.0*	
Female4	25.20%	14.06%	-11.14%	0.82	0.88	0.06	Economy	Gross Domestic Product (USD mn)	linear*	0.25	additive*	0.1	
Female6	9.11%	7.33%	-1.79%	0.72	0.76	0.05	Economy	Gross Domestic Product (USD mn)	logistic	0.01	multiplicative	0.1	
Hair1	15.72%	12.89%	-2.82%	0.53	0.58	0.04	Political	Foreign Exchange Rate: RBI: Reference Rate: Monthly Average: US Dollars (USD/INR)	linear*	0.10	multiplicative	0.1	
Hair2	16.64%	14.77%	-1.87%	0.12	0.27	0.15	Political	Trade Blance (USD mn)	logistic	0.05	additive*	0.1	
Hair3	19.09%	14.37%	-4.71%	-0.04	0.14	0.18	Economy	Gross Domestic Product (USD mn)	linear*	0.25	additive*	10.0*	
Hair4	27.49%	10.25%	-17.24%	0.00	0.28	0.27	Economy	Bombay Stock Exchange: Index: Fast Moving Consumer Goods: Month Average (01Feb1999=1000)	logistic	0.5*	multiplicative	10.0*	
Hair5	66.47%	35.17%	-31.30%	0.30	0.77	0.47	Economy	Wholesale Price Index (WPI) (2011-2012=100)	logistic	0.25	multiplicative	10.0*	
Health1	37.39%	28.52%	-8.87%	0.17	0.34	0.16	Economy	Consumer Price Index (2012=100)	logistic	0.01	multiplicative	0.1	
Health3	31.45%	21.27%	-10.18%	0.70	0.79	0.09	Climate	Temperature India: Monthly Median (Celsius)	logistic	0.01	multiplicative	1.0	
Health4	12.25%	9.67%	-2.58%	0.73	0.80	0.06	Climate	Humidity Monthly Median (%)	linear*	0.01	multiplicative	0.1	
Health6	28.11%	20.79%	-7.32%	0.70	0.73	0.03	Climate	Temperature India: Monthly Median (Celsius)	logistic	0.10	multiplicative	10.0*	
Oral1	19.88%	14.82%	-5.05%	0.06	0.22	0.16	Economy	Gross Domestic Product (USD mn)	linear*	0.5*	multiplicative	0.1	
Oral2	197.51%	54.03%	-143.48%	0.38	0.38	0.00	Economy	Gross Domestic Product (USD mn)	linear*	0.25	multiplicative	0.1	
Oral4	14.02%	11.39%	-2.63%	0.21	0.44	0.22	No Regressor	None	logistic	0.01	additive*	10.0*	
Oral5	16.89%	8.35%	-8.54%	0.69	0.80	0.11	Economy	Gross Domestic Product (USD mn)	linear*	0.5*	additive*	0.1	
Oral6	26.23%	23.78%	-2.45%	0.22	0.26	0.04	Economy	Bombay Stock Exchange: Index: Fast Moving Consumer Goods: Month Average (01Feb1999=1000)	linear*	0.5*	additive*	10.0*	Covid Excluded from Training
Personal10	22.40%	14.21%	-8.19%	-0.03	0.08	0.12	Economy	Gross Domestic Product (USD mn)	logistic	0.01	multiplicative	1.0	
Personal5	28.67%	15.26%	-13.41%	0.28	0.42	0.14	Climate	Humidity Monthly Median (%)	linear*	0.5*	multiplicative	0.1	
Personal6	14.97%	13.13%	-1.85%	0.04	0.08	0.04	Climate	Humidity Monthly Median (%)	logistic	0.05	multiplicative	0.1	
Personal7	20.15%	13.67%	-6.48%	0.19	0.31	0.12	Climate	Temperature India: Monthly Median (Celsius)	logistic	0.5*	multiplicative	1.0	
Personal9	23.55%	16.54%	-7.01%	0.14	0.29	0.15	Economy	Gross Domestic Product (USD mn)	linear*	0.01	multiplicative	10.0*	
Skin1	22.98%	17.07%	-5.91%	0.23	0.37	0.14	Economy	Bombay Stock Exchange: Index: Fast Moving Consumer Goods: Month Average (01Feb1999=1000)	linear*	0.25	additive*	0.1	
Skin2	29.78%	11.45%	-18.33%	0.19	0.47	0.28	Economy	Wholesale Price Index (WPI) (2011-2012=100)	logistic	0.01	additive*	0.1	
Skin3	18.54%	15.13%	-3.41%	0.06	0.33	0.27	Climate	Humidity Monthly Median (%)	linear*	0.01	additive*	10.0*	
Skin4	23.05%	16.25%	-6.79%	0.37	0.51	0.15	Political	Foreign Exchange Rate: RBI: Reference Rate: Monthly Average: US Dollars (USD/INR)	linear*	0.01	multiplicative	1.0	
Skin5	70.36%	40.07%	-30.29%	0.15	0.40	0.25	Economy	Wholesale Price Index (WPI) (2011-2012=100)	linear*	0.25	multiplicative	1.0	
Overall	32.79%	16.17%	-16.62%	0.35	0.50	0.15			42%	69%	67%	61%	
									* - Default Value				
Mean	32.79%	16.17%	-16.62%	0.35	0.50	0.15							
Median	22.62%	14.14%	-8.48%	0.25	0.43	0.17							
Mode	0.00%	0.00%	0.00%	0.00	0.00	0.00							
Max	197.51%	54.03%	-143.48%	0.87	0.96	0.09							
Halfpoint	103.31%	30.18%	-73.13%	0.37	0.52	0.15							
Min	9.11%	6.33%	-2.78%	-0.13	0.08	0.21							
Range	188.40%	47.70%	-140.70%	1.00	0.88	-11.81%							
Standard Deviation	37.83%	9.76%	-28.07%	0.31	0.28	-3.12%							
CV	1.15	0.60	-55.01%	0.88	0.56	-32.19%							

Table – B4

Hyperparameter Tally for Calibrated Runs

Growth	
Value	**Count**
linear*	21
logistic	15
Total	36
Changed from Default	**15**
	42%

Seasonality	
Value	**Count**
additive*	12
multiplicative	24
Total	36
Changed from Default	**24**
	67%

Growth Change Point Priority	
Value	**Count**
0.5*	10
0.25	10
0.1	3
0.05	2
0.01	11
Total	36
Changed from Default	**25**
	69%

Seasonality Priority	
Value	**Count**
10*	14
1	6
0.1	16
Total	36
Changed from Default	**22**
	61%

*** - Default Value**

APPENDIX C – VISUALIZATION DASHBOARDS

Figure - C1

Print Screen of the PowerBI Visualization Regressor Dashboard

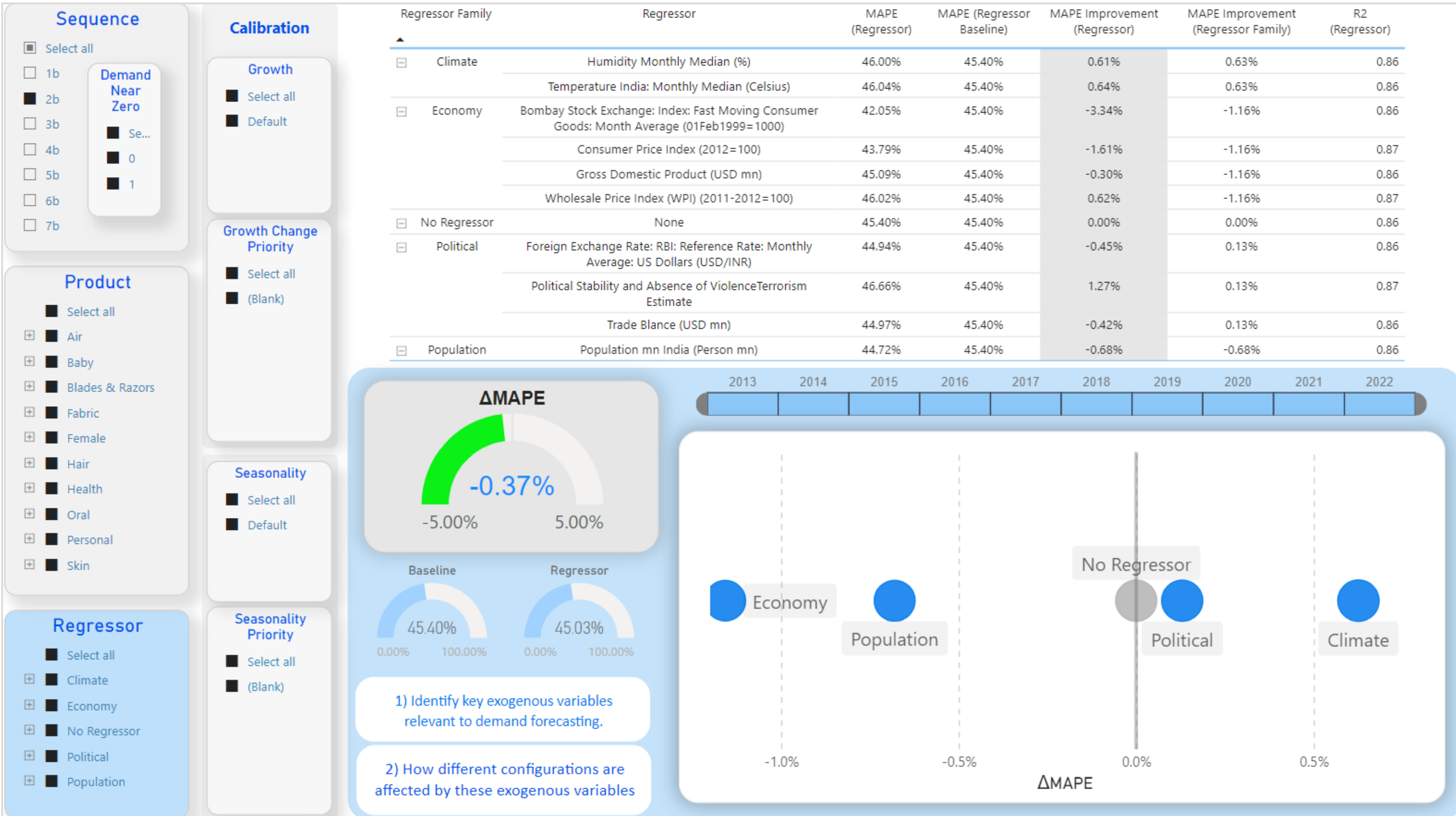


Figure - C1

Print Screen of the PowerBI Visualization Sequence Dashboard

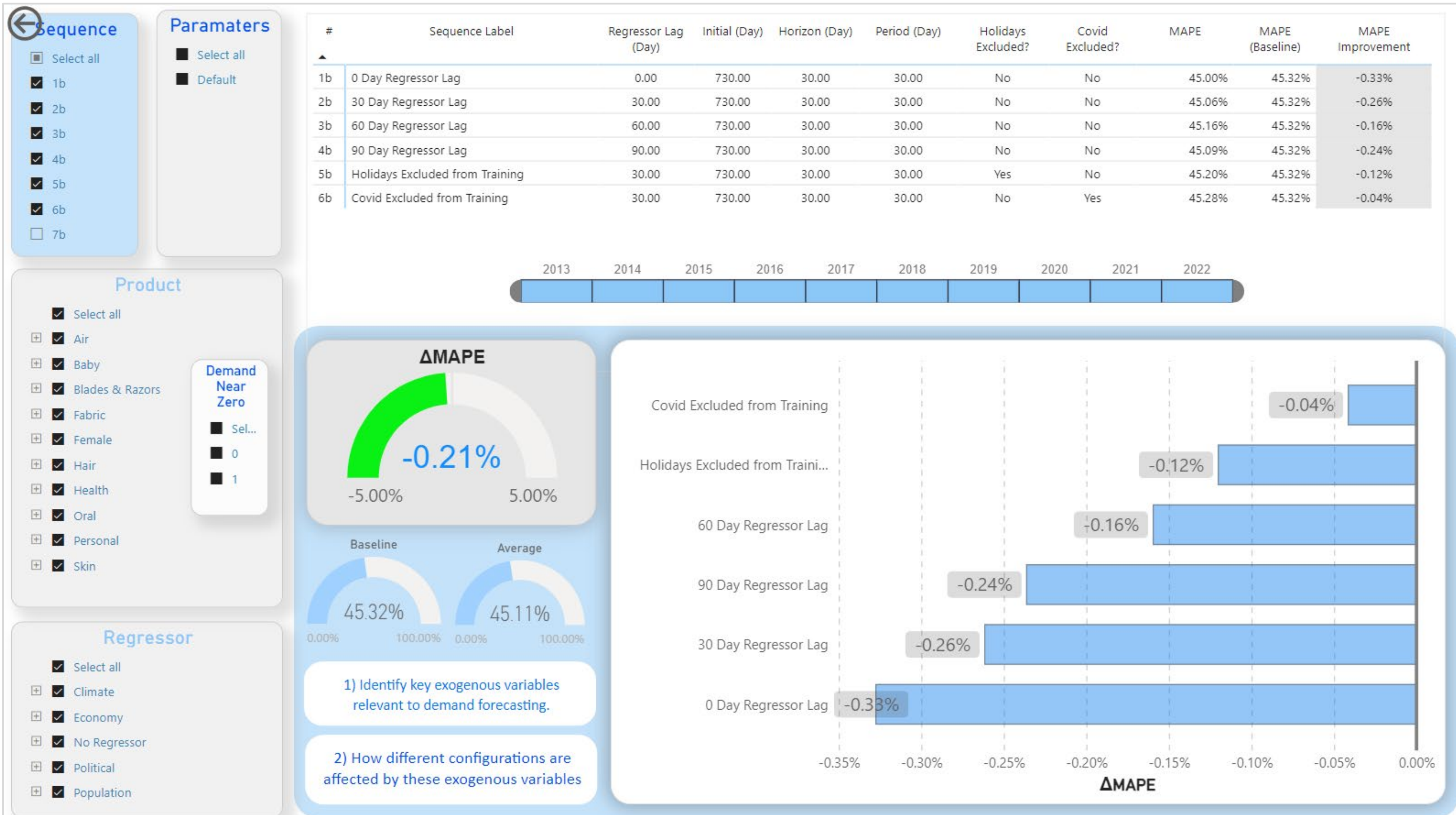
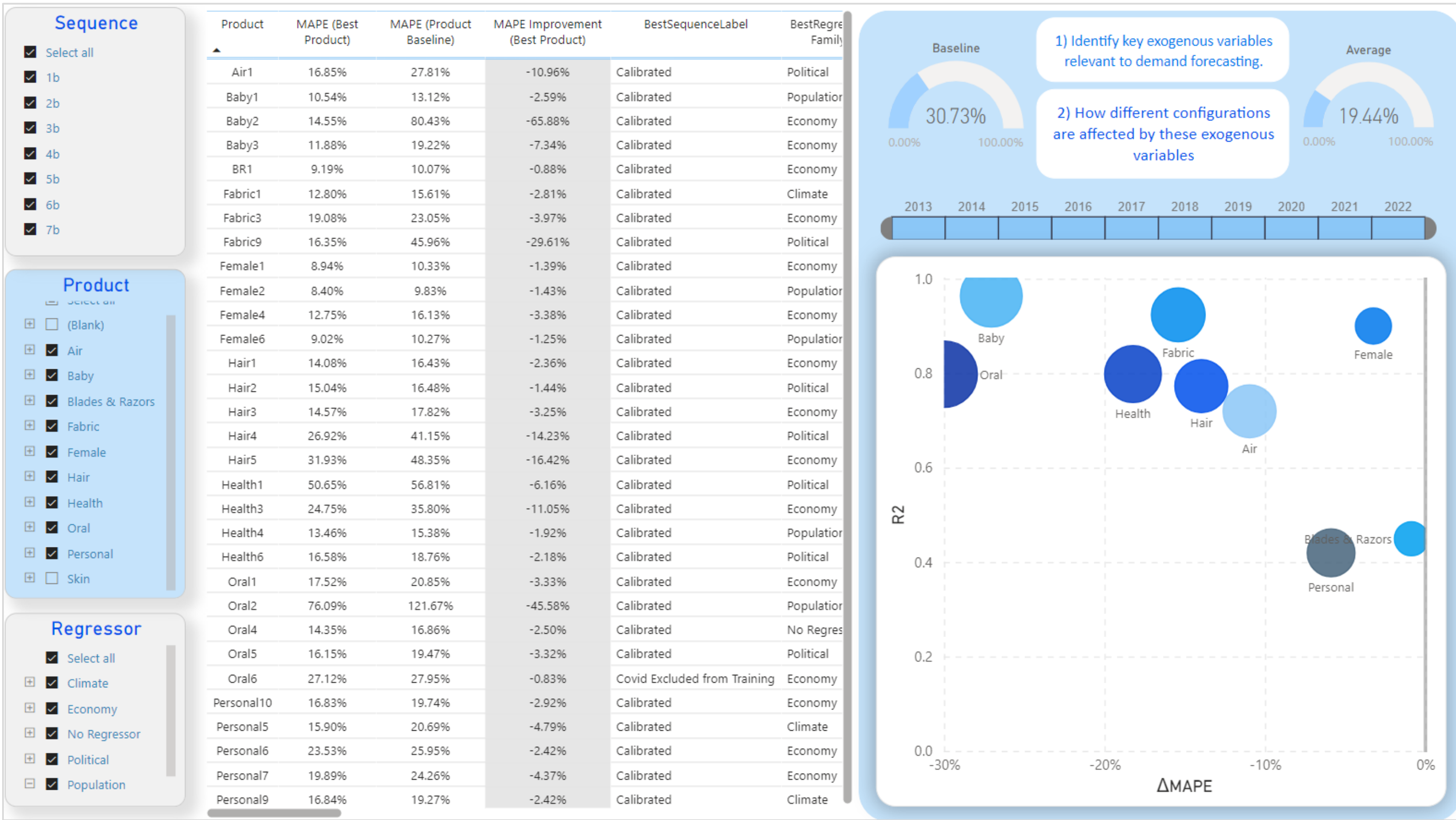


Figure - C1

Print Screen of the PowerBI Visualization Best Parameters Dashboard



Product	MAPE (Best Product)	MAPE (Product Baseline)	MAPE Improvement (Best Product)	BestSequenceLabel	BestRegre Famil
Air1	16.85%	27.81%	-10.96%	Calibrated	Political
Baby1	10.54%	13.12%	-2.59%	Calibrated	Populatior
Baby2	14.55%	80.43%	-65.88%	Calibrated	Economy
Baby3	11.88%	19.22%	-7.34%	Calibrated	Economy
BR1	9.19%	10.07%	-0.88%	Calibrated	Economy
Fabric1	12.80%	15.61%	-2.81%	Calibrated	Climate
Fabric3	19.08%	23.05%	-3.97%	Calibrated	Economy
Fabric9	16.35%	45.96%	-29.61%	Calibrated	Political
Female1	8.94%	10.33%	-1.39%	Calibrated	Economy
Female2	8.40%	9.83%	-1.43%	Calibrated	Populatior
Female4	12.75%	16.13%	-3.38%	Calibrated	Economy
Female6	9.02%	10.27%	-1.25%	Calibrated	Populatior
Hair1	14.08%	16.43%	-2.36%	Calibrated	Economy
Hair2	15.04%	16.48%	-1.44%	Calibrated	Political
Hair3	14.57%	17.82%	-3.25%	Calibrated	Economy
Hair4	26.92%	41.15%	-14.23%	Calibrated	Political
Hair5	31.93%	48.35%	-16.42%	Calibrated	Economy
Health1	50.65%	56.81%	-6.16%	Calibrated	Political
Health3	24.75%	35.80%	-11.05%	Calibrated	Economy
Health4	13.46%	15.38%	-1.92%	Calibrated	Populatior
Health6	16.58%	18.76%	-2.18%	Calibrated	Political
Oral1	17.52%	20.85%	-3.33%	Calibrated	Economy
Oral2	76.09%	121.67%	-45.58%	Calibrated	Populatior
Oral4	14.35%	16.86%	-2.50%	Calibrated	No Regres
Oral5	16.15%	19.47%	-3.32%	Calibrated	Political
Oral6	27.12%	27.95%	-0.83%	Covid Excluded from Training	Economy
Personal10	16.83%	19.74%	-2.92%	Calibrated	Economy
Personal5	15.90%	20.69%	-4.79%	Calibrated	Climate
Personal6	23.53%	25.95%	-2.42%	Calibrated	Economy
Personal7	19.89%	24.26%	-4.37%	Calibrated	Economy
Personal9	16.84%	19.27%	-2.42%	Calibrated	Climate