

A Work Project, presented as part of the requirements for the Award of a Master's degree in International Management from the Nova School of Business and Economics.

A new way of implementing prices - a Dynamic Pricing Strategy in E-commerce

**CAROLINA CLODE SILVA
RODRIGUES VALENTE**

Work project carried out under the supervision of:

Elizabete Cardoso

16/01/2023

This work used infrastructure and resources funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209).

Abstract

Dynamic Pricing is an emerging subject that has been deeply explored during the Covid19 pandemic. The project Dynamic Pricing Model in E-commerce consists in designing a challenging model to apply to the Navigator Hub (digital platform), as prices are still manually adjusted. “Does customer data analytics from the online channel suggest there is room for customer differentiation in real time?” is, therefore, the key research question. The main focus was on one possible variable for the model, a cluster analysis using IBM SPSS. Four segments, exhibiting different customers’ patterns, arise from there, thus, confirming there is margin to adjust prices.

Keywords: E-commerce, Digital, Strategy, Revenue, Business to Business, Online, Cluster, Client.

This work was supported by Nova School of Business and Economics and The Navigator Company.

I would like to thank Maria Barreto de Lara, David Vieira Antunes, Cristina Campos, and Eduardo Veiga, from The Navigator Company, as well as to my advisor Professor Elizabete Cardoso, from Nova School of Business and Economics.

Table of Contents

1. INTRODUCTION	4
a. Company overview	4
b. Industry overview	5
2. LITERATURE REVIEW	6
a. Pricing decisions in emerging markets.....	6
b. Dynamic Pricing Model	7
c. Main goals and future achievements	7
d. Benefits and Drawbacks	8
e. Challenging the Business-to-Business context	8
f. Commodity Markets	10
g. Possible solutions and alignment in the organization	11
h. Determining the appropriate variables	11
i. Implementation process and algorithm analysis	12
j. Limitations	13
k. Dynamic pricing in different industries	14
3. DATA COLLECTION AND METHODOLOGY	15

a. Micro and Macro levels of Data	15
b. Clustering process	16
c. Data applied to The Navigator Company	17
d. Process description	19
4. ANALYSIS AND DISCUSSION	20
a. Segmentation and Clusters composition	21
b. Clusters characterization	24
c. Final results and Cluster denomination	25
5. RECOMMENDATIONS	26
6. CONCLUSION	27
7. REFERENCES	28
8. APPENDICES	32

1. INTRODUCTION

a. Company overview

The Navigator Company is an integrated producer of forest, pulp, paper, tissue, and bioenergy, whose business is leveraged by state-of-the-art factories on a worldwide scale, with cutting-edge and sophisticated technology.

The Company's business model revolves around a raw material of excellence – Eucalyptus globulus – whose intrinsic features allow a strategy of differentiation to be pursued, based on high-quality products. This allows Navigator to be an international benchmark in its sector.

Thus, the Company is the largest manufacturer in Europe of uncoated wood free paper (UWF) for printing and writing (the category that includes office paper) and the 6th largest producer worldwide. It is also the leading European manufacturer of bleached eucalyptus pulp (BEKP).

From a national perspective, it is the Portugal's third-largest exporter, accounting for approximately 1% of the country's GDP and around 2,5% of all exports of national goods.

Navigator markets products under various brands, including Pioneer, Inacopia, Explorer, Inaset, Soporset, Target, Discovery, and Navigator (the global best seller in the premium office paper segment). The company operates several industrial manufacturing facilities, including Setúbal, Figueira da Foz, Aveiro and the Vila Velha de Rodão pulp and paper mill. It also offers production planning and logistics services. Additionally, the company operates in 130 countries across the five continents, and it has its headquarters located in Setúbal, Portugal.

Navigator currently has six business units, including Research & Development, Agro-Forestry,

Pulp production & sales, Paper production & sales, Tissue production & sales and Energy.

b. Industry overview

The paper industry has been undergoing a huge transformation, mainly during the last years.

Major changes in physical stores and e-commerce, as well as innovative prospects for new growth have been made across the paper and forest-products industry, in order to face the lower global demand. However, according to *Appendix 1*, the global paper and paperboard industry continues to grow, despite a decline in the graphic-paper segment.

Companies in this sector have been analyzing new innovative ways to boost their profitability.

Packaging, tissue papers, pulp for hygiene products and for textile applications are the more recent trends that involve sustainability matters and, thus, have been growing around the world.

Following some research, graphic papers continue to face a worldwide decline in demand by around 7,6%, which tends to be accelerating and, thus, it requires innovation and a restructure of the production capacity. Consumer packaging and tissue, as well as transport and industrial packaging are value-creating sectors with opportunities to grow even more, through demographic shifts and consumer trends. Also, fiber has been facing turbulent times and some volatility in prices, spreading across different locations.

Therefore, connecting sustainability requirements, e-commerce, and technology integration require facing future challenges. The board of companies should be concerned about finding the next level of cost optimization and value-creating growth roles for forest products. In this constantly changing business, increasing relevancy in the packaging world, and finding the right

path in next-generation bio-products are crucial matters to develop this industry that seemed to be disappearing (Berg and Lingqvist 2019). It is also fundamental to ensure the right offer is available to the right customer at the right time, and this implies examining customer data on the one hand, and dynamic pricing models, on the other hand.

The study aim of this project is therefore to explore - and materialize, where possible - the opportunities for applying dynamic business pricing in Navigator's online channel. The next section, Literature Review, will then include a detailed knowledge and researched about the main benefits, drawbacks, and limitations of this pricing strategy as well as, pricing decisions in Business-to-Business context and commodities industries. Furthermore, some solutions/different models and the implementation process (including potential variables) will be discussed. Afterwards, in methodology, through the historical sales data of the Company, a clustering analysis in IBM SPSS will be done in order to find the best clients' segments for the company, that will lately constitute a variable for the whole model, indicating in which of them prices could be set slightly above or below. These segments are going to be discussed in "Analysis and Discussion" section, while presenting valid reasons and rationales for their similar behaviors. Lastly, some recommendations on other potential global variables to be included in the model, as well as main conclusions will be gathered to present to the Company.

2. LITERATURE REVIEW

a. Pricing decisions in emerging markets

With the increasing complexity of the markets, pricing decisions are not static and more

challenging, therefore, there is the need to continuously analyze the market and the competition. As a consequence, many companies are adopting computerized pricing support systems (Phillips 2021, Chapter 2.4.3). Dynamic pricing consists of the utilization of Artificial Intelligence to establish different prices for the same product to different customers, depending on exclusive personal and global factors (Enache 2021, 1). This high-tech and fast spreading pricing strategy is mainly utilized in the e-commerce sector, where companies can collect market data and adjust the products' prices to the customers' willingness to pay. In this sector, according to *Appendix 2*, more than 35% of companies in North America and Europe either use this model or plan to use it, soon (Dearth 2022).

b. Dynamic Pricing Model

The concept of dynamic pricing was introduced during the 1980s by the airline industry. After that, in the 1990s, the internet and new technologies emerged, incentivizing hotels to implement this price strategy as well. Later, by 2000, e-commerce was introduced, making huge improvements in the dynamic pricing model, by Amazon and eBay (Baldwin 2019). Nowadays, dynamic pricing is a well-known and successful topic that is very demanding in digital platforms, across many different industries (for instance, in the retail environment). It has emerged exponentially since the Covid19 pandemic, not only in online channels, but also in offline ones. Researchers have been studying and analyzing strategies and approaches to successfully implement this model in the e-commerce era.

c. Main goals and future achievements

There are goals that enterprises want to achieve when using dynamic pricing models, that are mainly to predict the prices that each customer would pay for a product and to have a fast response to market fluctuations. Consequently, the company's profitability will increase, as well as customer engagement and loyalty (Enache 2021, 1).

This pricing module has been proven efficient in increasing levels of customer satisfaction and, consequently, promoting sales growth (at least 2%-5%) and sales margins improvement (at least 5%-10%), as illustrated in *Appendix 3* (BenMark, Klapdor, Kullmann, and Sundararajan 2017).

d. Benefits and Drawbacks

As successfully proved, there are many advantages of this type of pricing model, and they are related to both the company's performance indicators and customer satisfaction. This model allows the company to make quick price reductions and to adjust its prices based on an individual customer's likelihood of purchasing a product, instead of the market (Biscontini 2020). Also, the use of Artificial Intelligence to establish prices (through elastic or competitive models) allows the company to get market information, that can be used to analyze consumer behavior and make better marketing decisions, rather than pricing (Enache 2021, 3).

However, negative aspects may also arise. There is always some level of uncertainty about customers' responses to different prices (Enache 2021, 3). In addition, this strategy may lead to unfair discrimination between consumers and boost collusion between firms, which can then lead to an increase in prices (Thornhill 2022).

e. Challenging the Business-to-Business context

According to Fatemeh Goli and Manijeh Haghighinasab, the dynamic price has received relatively little attention in the Business-to-Business environment. It was an under researched topic that, however, has been growing during this new digital era (Goli and Haghighinasab, 2021, 14).

B2B situations are particularly different from B2C ones. In the first case, sellers can easily vary prices, not only across buyers, but also between subsequent purchases of the same buyer. In addition, trust and commitment between sellers and buyers are crucial to determine long-term and stable relationships between them. That is why prices also have long-term effects in B2B markets. In general, transactions can be more complex and exceptional situations, such as a pandemic, can influence buyers' decisions. Overall, in this business environment, decision makers (meaning, buyers and sellers) are assumed to behave rationally, which might be different in B2C cases (Zhang, Netzer and Ansari 2014, 1).

Therefore, making pricing decisions in B2B situations can be very challenging. Firstly, pricing must consider "unobserved random shocks", such as demand boosts or supply shortages. Secondly, maintaining confidence and commitment across all decision makers' relationships can be difficult due to environmental uncertainty. Moreover, segmenting and targeting B2B markets evolves a lot of variables' analyses. Segmenting depends on customer size, industry, customer behavior and buying behavior, whereas targeting carefully analyses the price sensitivity of each buyer, splitting them between "programed" and "transactional" buyer (Zhang, Netzer and Ansari 2014, 3). Thus, changing price decisions in a B2B operational

company requires adaptability, market research and alignment between all the departments. Companies should focus on who is responsible for what, how to make appropriate discounts (right parameters), as well as aligning them across the organization (Phillips 2021, Chapter 2.1).

f. Commodity Markets

Regarding the commodity industry, there are some multinational companies that are already using dynamic pricing strategies, for instance, Walmart and Amazon, or even gas stations (Morenne 2022). However, it is still an underexplored topic due to the high volatility in commodity prices. Companies in this business must spend a large amount on fixed assets to turn raw materials into finished products. Therefore, their products compete on price and differentiation (Bank 2022).

Global macroeconomic shocks, such as the pandemic recession, faced demand shrinkages and supply disruptions which, in turn, lead to a collapse in the commodity prices, as it can be seen in *Appendices 4 and 5* (Vasishtha 2022).

Consequently, a Commodities Factor Model (CFM) has been improved as a dynamic factor model, for a large cross-section of energy and non-energy commodity prices. The model is decomposed according to *Appendix 6*, and it relies on available market data, making it easier to maintain and adjust prices and/or groupings. Thus, it imposes a block programming structure on the factors that decompose the price movement of each commodity into a global, block or idiosyncratic component. The global factor captures price trends that are common to all included commodities, whereas the idiosyncratic captures supply shocks and block factors

capture both supply and demand elements. All combined, the model aims to describe commodities price variability, providing meaningful economic interpretations, which can be helpful when applying dynamic pricing in commodities industry (Bilgin and Ellwanger 2017).

g. Possible solutions and alignment in the organization

If a company thinks about moving to a dynamic pricing solution, analysts, category managers and pricing managers must meet and align a full structure of the process. They are the ones responsible for the development and roll-out of the tool.

According to Mckinsey, there are five different modules that should be included in this mechanism: the long-tail module (to help retailers setting introductory prices for new products), the elasticity module (to understand how prices affect demand), the Key Value Items module (to estimate how much each product affects consumer perceptions about the prices), the competitive-response module (to adjust prices according to competitors' prices), and the omnichannel module (to coordinate prices in online and offline channels) (BenMark, Klapdor, Kullmann, and Sundararajan 2017).

h. Determining the appropriate variables

When starting the process, there are tons of variables to study and define. Starting with supply and demand, analysts and managers should look at stock levels, current costs, future cost predictions, as well as product page views in digital platforms and product seasonality, respectively. Additionally, it is crucial to benchmark about competition prices, substitute products' prices and data about specific customers (for instance, number and method of

purchase events, location, day and time of the day, quantities, and quote price) (Dilmeganiz 2022). Relational factors, such as relationship quality, trust, or commitment, must also be considered. Lastly, economic and market volatility (as in commodity markets) is a huge indicator that constantly influences decision makers. All these combined and estimated will lead to an exhaustive and lengthy interpretation process.

i. Implementation process and algorithm analysis

Implementing a dynamic pricing model, as previously mentioned, requires digital analytics software/machine learning to scan and interpret large volumes of data (Biscontinini 2020). Basically, it consists of finding the right pattern that connects the input data to the target price. Along with it, market analysts must focus on price changes, analyze possible competition, and get a lot of historical sales data (product details), in order to adequately set products prices by estimating demand, as they no longer depend only on stocks (Enache 2021, 3). After collecting market data, the company needs to think of which dynamic price module to apply, depending on product categories available. It can be flat dynamic pricing (generally, increasing or decreasing prices according to predetermined factors), individualized dynamic pricing (depending on customers profiles), or even a hybrid approach of these two (Kampakis 2019). The last step would be to apply the dynamic price algorithms to the gathered data. This will lead to different price ranges but more accurate results. In addition, data should be updated and optimized to get real time one (Dilmegani 2022).

The main goal of the last step is to maximize sales while operating in an unknown environment

(Enache 2021, 4). As it was previously said that many variables should be taken into account when thinking of applying new pricing decisions, the same happens with algorithms. They include pricing optimization variables, such as price management automation, profitability analysis, price forecasting, price competition market analysis, customer analysis, among many others. Furthermore, a typical dynamic pricing algorithm follows the next four phases. Firstly, it analyzes competitive price points, historical sales data, and market demand. Secondly, it identifies a possible interdependence in demand points. Thirdly, it calculates accurate estimations and optimal prices, through mathematical models and the respective variables. Lastly, the algorithm informs the prices and continually reruns the equation for the latest repricing results (Dearth 2022).

j. Limitations

As in every model, constraints are part of it, but it is important to understand and try to overcome them. In order not to lose confidential data, companies should choose cloud-based solutions (instead of in-house systems), which will increase costs. Furthermore, the software chosen needs to be compatible with the existing company's internal system. Also, different price options and subscription methods should be carefully analyzed to see which one fits the best for the firm.

In addition to this, dynamic pricing cannot be implemented manually, as it involves large amounts of real-time data, and it is executed on a big scale. Overall, it requires advanced algorithms and organizational flexibility to act quickly, with regards to dynamic pricing

decisions and solutions. It is important to be aware that it is a continuous process, which means a constant revision and investigation need to be done, in order to obtain higher returns (Dilmegani 2022).

k. Dynamic pricing in different industries

Nowadays, dynamic pricing is present in many different industries, and it is expanding even more. For example, in industries where imperfect competition prevails, companies typically can retain some pricing power. Thus, dynamic pricing models would be more appropriate and realistic, rather than models based on stock control (Ke, Zhang, and Zheng 2019, 1). They are currently a standard practice across dissimilar industries, even if their main core is online and/or offline (Phillips 2021, Chapter 14).

In fact, before e-commerce exploded in the last years, airlines and hotels, as well as car rentals and gas stations firms, were already implementing or using dynamic prices. These hospitality industries are highly dependent on seasonality, which made them adapt their pricing strategy.

Furthermore, retail companies with physical stores were also managing their prices, in order to obtain better financial outcomes. Retailers can set their own prices, mainly according to competitors' prices, cost of goods and willingness to pay. E-commerce, a more recent trend, is currently investing more and more in these types of models, as they have been proven a success in some companies, such as Amazon, Walmart, Uber, and eBay (Dilmegani 2022).

After searching in detail about the dynamic pricing subject and how this can influence business models, by using different articles and papers from different sources, the uncertainty about how

this can actually be applied to The Navigator Company still remains open. Therefore, the main research question to be analyzed in the next sections is “Does customer data analytics from the online channel suggest there is room for customer differentiation in real time, i.e., dynamic pricing models? If so, how can it be put in place?”.

3. DATA COLLECTION AND METHODOLOGY

Following an inductive and positivist knowledge perspective, secondary data from The Navigator Company was analysed to reach to a final dynamic pricing model recommendation and, thus, no survey was needed to be conducted. This data consists in online historical sales data, from March 2021 (date of the online platform launch) until the moment (October 2022), that will be further detailed later. This quantitative research, based on available data and conducted in IBM SPSS, aims to build a cluster analysis, which will then be included as a variable in the dynamic pricing model. Overall, the main goal is to have an individualized dynamic pricing (focusing on customers’ profile) that sets the optimal price for each cluster.

a. Micro and Macro levels of Data

For the company business model to quickly adapt to market fluctuations, big data (including structured and unstructured data) is a key resource to explore. While developing a machine learning-based price optimization, it is crucial to include both micro and macro levels of data. The first one includes internal and static historical data to recognize the real demand flow and unique customers’ characteristics, whereas the second one considers the external and dynamic market data that can be crucial to determine the optimal prices (Ramesh 2021).

According to some studies, even though micro data (when available) should have priority over the macro data, quality, and quantity of data matters to overlook factors that were not being considered before (Vouk 2018).

b. Clustering process

Regarding the cluster analysis, the purpose is to respond to customers in a more individual way.

As some clients are more price sensitive than others, segmenting them according to different internal and external variables is critical for dynamic pricing to be successful. In the long term, this will enable the Company to create more value for both the business and its consumers, ensuring profitable growth.

After receiving the data collection from the Company, the first step was to identify a group of customers according to their purchase patterns and some other variables (described in *section c.*). The clustering will then bundle the customers with similar behaviors in response to a pricing decision (Nidhi 2022).

Following a careful analysis on the different types and methods used in clustering, the hierarchical clustering type was considered the most appropriate one, taking into account the low-medium volume of the dataset and the quantitative and qualitative variables used. It is based on the principle that every object is connected to its neighbors depending on their proximity distance. In addition, it was decided to use a top-down approach (divisive approach), where all the data points belong to one large cluster (online clients) and the goal is to divide it into smaller groups, according to their purchasing characteristics (Joshi 2022). Hierarchical

clustering is, therefore, easy to implement and it provides accurate results. Also, unlike other clustering types such as K-means, there is no need to define the number of clusters in the beginning of the analysis. However, execution time can be high and, sometimes, it is hard to determine the accurate number of clusters from the output (Gupta 2022).

Furthermore, the method selected was the Ward's method (considering, at first, n clusters, each containing a single object), measured using squared Euclidean distance which simply considers the points “a” and “b” as the furthest vertices of a right triangle and takes the hypotenuse of the triangle as the distance, as following: **Euclidean Distance (vectors)** : $d(a, b) = \sqrt{\sum_i (a_i - b_i)^2}$.

Besides the fact that, while squaring the distance, the effect of outliers can be amplified, it seems a suitable and understandable way that is graphically straightforward (Sohail 2018).

At the end, the platform generates a dendrogram, illustrating groups of clients with purchasing behavior similarities, which should be considered for the dynamic pricing model.

c. Data applied to The Navigator Company

The historical sales data received from the Company contained daily transactions data from 182 clients (*see Appendix 7*) who bought online. It included both the client's name and the respective client ID that will constitute the clusters. From a **micro level data** perspective, the data includes the variables demonstrated in *Table 1*.

Table 1 – Variables included in the historical sales data provided by the Company

Variable	Description
Market	It shows the country or region where the client is located, as in <i>Appendix 8</i> .
Client group	It demonstrates if each client is inserted in a larger group, or not. Group clients are presented in <i>Appendix 8</i> .
Customer type	It presents the type of customer (for example, if it is a retailer or a wholesaler), as detailed in <i>Appendix 8</i> .
Order number	It indicates the order number for internal purposes.

Product type	It indicates the product code (there are around 800 codes) to internally observe the product attributes.
Product format	It presents the format bought for each product (cut size, folio or reems).
Strategic Brand	It includes the three main brands (Mill brands, Mill wrappers and Col's).
Brand group	It is a subgroup of the Strategic Brand that includes 41 brand groups, as detailed in <i>Appendix 8</i> .
Brand name	It is a subgroup of the Brand group that includes 127 brand names, as detailed in <i>Appendix 8</i> .
Grade	It indicates if the product bought was from a Premium, Standard or Economy segment.
Invoice date	The day, month, and year when the invoice was issued.
Quantity	It represents the total quantity, in kilos, requested in each order.
Price unit	It represents the final price in euros, per unit (kilos), for each different product.
Total amount paid	It represents the total amount paid by the customer for each order. It was calculated by multiplying the quantity times the price unit.

All these variables gave information to the IBM SPSS program to identify similar behaviors between customers and, consequently, group them. However, as the data was provided by order (1490 transactions), some adjustments had to be made in order to transform the variables to columns, aggregating clients by line, with some reasoning behind. Thus, from a **macro level data** point of view, the set of 17 variables described in *Table 2* were derived from the historical sales data (by using formulas, further research, and internal discussions), in order to add some of them to the clustering analysis to get more accurate results.

Table 2 –Variables to be included in the dataset for IBM SPSS

Variable	Segmentation Technique	Reasoning
Market (not included for clustering)	Geographical	Each client is located in one market. Depending on where it is located, it might influence its cultural purchasing behaviors. This is a qualitative variable; thus, it will be considered in section 4, only while characterizing each cluster.
Client group (not included for clustering)	Behavioral	The goal is to see whether or not each client is inserted in a group. Being in a group can provide some discounts or lower prices as there are more people buying more products (volume). This is also a qualitative variable; thus, it will be considered in section 4, only while characterizing each cluster.
Customer type (not included for clustering)	Behavioral	Depending on what will be the final use of the product, different customer types will behave differently. This is also a qualitative variable; thus, it will be considered in section 4, only while characterizing each cluster.
Order number	Behavioral	The purpose is to identify the frequency in which each client buys,

		through the number of orders.
Product format	Behavioral	Buying paper cut size or reels will definitely affect the volume that need to be produced and the revenue of the Company. Therefore, the objective is to understand what the customers preferences are and what they are used to buy, in terms of volume/quantity of each format.
Strategic Brand	Behavioral	As different brands represent different quality of the paper and, thus, different prices, this variable will characterize the brand loyalty for each client. As with product format, quantities were discriminated across the 3 strategic brands.
Grade	Behavioral	It has the same rationale as the previous ones, meaning, quantities were divided between the 3 grades.
Invoice date <i>(Month not included for clustering)</i>	Behavioral	The objective is to calculate how many days have passed since the last purchase date from now (October 2022). Thus, it will evaluate the recency interaction of each client. The lower the value, it means that the client ordered recently. Also, by checking in which month each clients orders the most, we can observe if there is seasonality. This last qualitative variable will be considered in section 4, only while characterizing each cluster.
Quantity (kg)	Behavioral	Computing the average quantity per order to determine what are the clusters with higher volume for the Company.
Price unit (euros)	Behavioral	This will enable us to check the maximum, the average, and the minimum final unit price that each client is willing to pay.
Total amount paid (euros)	Behavioral	First, to calculate the average amount paid per order. Secondly, to calculate how much each client had contributed to the Company's revenues, since March 2021.

Geographical segmentation technique will consider a division of the clients into different geographical locations (for instance, country), whereas the behavioral segmentation is based on customer's needs and subsequent reaction towards purchasing (for example, regularity of purchase).

d. Process description

After selecting all the variables from the data provided, as they were expressed in different measures, it was necessary to make it more comparable before uploading in IBM SPSS, by reducing the scale effects. Thus, the final data was standardized by converting the results into z-scores and to a scale of 1-100, as presented in the following formula: $X'_{ij} = \left[\frac{X_{ij} - \min_i}{R_i} * 99 \right] + 1$

X_{ij} corresponds to the average score of clients j on variable i ; X'_{ij} is the scaled final value of

client j for the variable i ; $\min_i$ is the minimum value for the variable i ; and R_i is the range of variable i . In addition, as not all the variables had the same impact while building the clusters, different coefficients were attributed to the 17 variables, adding up to a total weight of 100% (as described in *Appendix 9*). This allocation was based on the relevance of each variable to the purchasing behavior analysis of customers, as internally discussed with the Company. Firstly, variables were divided in groups (“General Variable”) and attributed a high, medium, or low importance level (“Total percentage”). After a detailed analysis, each individual variable was assigned with an individual coefficient. High coefficients were given to Strategic Brand and Grade (27% each) that clearly define what each customer prefers to buy, according to its budget. Then, medium level of importance was assigned to Product format (only 9%, as it is less relevant compared to the next general variable) and Quantity & Price (25%, where some variables, such as maximum and minimum unit price, have higher coefficients due to the price sensitivity). Lastly, the number of orders and purchase date were considered as low. Orders, for example, are relevant to observe the frequency of purchases but, as examined, a client can have a lot of orders but lower quantities per order, which could negatively influence the clustering. At the end, each variable was multiplied by the respective coefficient attributed, providing the final file to IBM SPSS.

4. ANALYSIS AND DISCUSSION

In order to find out if customer differentiation and price adjustments in real time can be applied to The Navigator Company, it is crucial to understand its current situation. Therefore, a SWOT

analysis was made, as presented below. Following the pricing strategy threat, a clustering analysis is going to be characterized and discussed for the future dynamic pricing model.

Table 3 – SWOT analysis

STRENGTHS	WEAKNESSES
Leader in the UWF Paper Premium segment	Forestry based business, which can be highly dependent on weather conditions
Nursery of plants, being able to produce its raw materials from scratch	Highly dependent on machinery
Research & Development Institute (RAÍZ)	The production units are concentrated in Portugal, which can be difficult with logistics, particularly exportation
Vertical Integration, that results in lower operational costs and very efficient operations	Prices are continuously adapted manually, even after de Navigator Hub online platform was launched
OPPORTUNITIES	THREATS
Pulp, Tissue and Renewable Energy growing markets	Structural decline of Graphic-Paper market (Digital Era, paper is becoming obsolete)
Increase capability of production and expanding business: Tissue, Pulp and Packaging	Environmental Legislation (forest usage limitations) and Disasters (for instance, fires)
Mozambique Projected nursery, increasing raw material production	Semapa high dependence in Navigator dividends

Following section 3, combining all the information in the IBM SPSS platform, the output (dendrogram, as in *Appendix 10*) set 4 clusters/segments out of 182 customers (detailed in *Appendix 11*). The main Research Question, as briefly stated above, is to observe if there are different customers profiles in the e-commerce platform and how they can affect the opportunities of the company to implement and succeed using a dynamic pricing model. Therefore, this chapter will include a description and characterization of the clusters, as well as a discussion and presentation of the final results.

a. Segmentation and Clusters composition

According to the input given to IBM SPSS, meaning the variables related to Quantity, Price, Frequency and Recency, clusters were divided as shown in *Table 4*. It is important to mention

that only 2 clusters were initially proposed by the platform. But, after running different possibilities, these analyses were presented to the Company. Considering the segmentation purpose, as well as, future implementation actions, it was internally agreed that the best effective solution was the one with 4 different customers' profiles, aiming for different prices.

Table 4 – Clusters composition

Clusters	Percentage	Number of Clients
1	49%	89
2	41%	75
3	8%	15
4	2%	3
Total	100%	182

Cluster 4 only represents 2% of the total customers and Cluster 1 includes almost 50% of them.

Therefore, there is a huge discrepancy among them that is going to be further explained.

Table 5 – Quantity analysis

Clusters	Total Quantity (kg)	Average Q per client	Average Q per order
1	33 013 581,0	370 939,1	8 625,3
2	8 734 543,0	116 460,6	13 892,5
3	531 529,0	35 435,3	9 322,5
4	15 799 172,0	5 266 390,7	16 179,6
Total	58 078 825,0	319 114,4	10 977,8

Firstly, about Quantity, it can be observed that Cluster 4 has both the highest average quantity per client and per order. Cluster 1 presents the highest total quantity (57%), but also the highest number of clients, which then leads to lower quantities per client and per order. Lastly, Cluster 3 seems to be the worst segment in this variable.

Furthermore, looking at Strategic Brands and Grades, as in *Appendix 12*, Cluster 4 achieves the highest volumes in all of them. Also, the average quantity of Mill Brands is higher than the other two strategic brands, as well as the average quantity of Premium compared to Standard and Economy. Generally speaking, clients are brand loyal and prefer higher paper quality.

Table 6 – Price unit analysis

Clusters	Average of Maximum price	Average of Average price per unit	Average of Minimum price
1	1,4	1,1	0,9
2	1,4	1,3	1,3
3	1,0	0,9	0,9
4	1,6	1,1	0,8
Total	1,4	1,2	1,1

Looking at final Price unit, Cluster 2 displays the highest average and minimum price per unit, meaning it might be willing to pay slightly more. That is why this cluster does not buy economy products (see *Appendix 12*). Clients from Cluster 3 are probably more concerned about costs; thus, it is considered the cluster that is willing to pay less, mainly due to the lowest maximum price per unit. Regarding Cluster 4, it is the one that pays the higher maximum price per unit, on average. One reason might be brand and grade loyalty. However, it can also pay the lowest unit price (maybe because higher quantities sometimes lead to lower prices through discounts). According to *Appendix 13*, total amount paid in each cluster seems to be aligned with the quantity purchased. For instance, Cluster 3 is the one who buys less quantities, thus, it spends less money, on average, on its orders.

Table 7 – Frequency and Recency analysis

Clusters	Average of Number of orders	Average of Nr of days since last purchase
1	47,2	27,4
2	8,6	24,8
3	4,9	402,2
4	317,3	3,7
Total	32,2	56,8

Lastly, an analysis was made to understand which clusters buy more frequently and recently. Looking at the second column, Cluster 4 is the one that buys more frequently as it has the highest average number of orders per client (317) until the moment (October 2022). In contrast, Cluster 3 does not seem willing to make a lot of orders (5), therefore, it is composed by less regular clients who do not actively go to the portal but, when they do, they buy more quantity

per order (comparing to Cluster 1).

On the other hand, Cluster 4 is also the one that bought more recently (only 4 days have passed since the last purchase). Also, Cluster 3 is composed mainly by old clients who bought in the beginning of the period but have not been buying recently (more than a year ago). One of the reasons may be the slower adaptation to the NVG Hub or that they prefer other order methods.

b. Clusters characterization

After receiving the clusters output, it was possible to see in *Appendix 14* a seasonality pattern.

On average, clients make additional purchases in June, July, and September. In June and July, clusters are composed by clients who probably prepare beforehand the start of the year.

In addition, cluster's location is distributed around the world, according to *Appendices 15* and *15.1*. Cluster 1 is mainly composed by clients from Spain (45%) and some from Portugal (34%); Cluster 2 is mostly constituted by clients from Spain (32%) and Italy (28%); Cluster 3 has 67% of Spanish customers and, Cluster 4 includes two clients from Portugal and one from UK.

Looking at customer type (*Appendices 16* and *16.1*), it indicates a huge dispersion across the four clusters. Each of them is concentrated in around three different types of customers, however, they do not seem to have any common pattern. For instance, in Cluster 4, who is composed only by three clients, each of them represents a different customer type.

Paper merchants, who represent 20% of clients, are more concentrated in Clusters 1 and 2.

Wholesalers, representing 23% of total clients, are more focused in Clusters 1 and 3.

Lastly, considering *Appendix 17*, clients who belong to a group (client with a larger size) are

mainly concentrated in Clusters 1 and 2 (31), more diverse segments. Therefore, being inserted in a group might not influence clients' purchase behaviors as, in Cluster 4, who is composed by active portal customers bringing massive volumes, they do not belong to any group.

c. Final results and Cluster denomination

According to all the previous information, names were established for each cluster. Cluster 1 is the largest segment, composed by clients who prefer Mill Brand and Premium grade over the other two options, but they are used to buy lower quantities per order. In addition, they might not like adjustments and/or changes in prices because it presents a low minimum price unit (0.9). So, it was named as "Diversity and Price Inclusive". Overall, judgments and conclusions arising from this cluster may be considered more biased and uncertain due to the huge variety of clients' sizes, when compared to the other clusters. Cluster 2 was entitled as "Premium Quality" as these clients do not buy any Economy products (as shown in *Appendix 12*). They care about paper quality and, in general, they are willing to pay more for each product. Therefore, reaching out them can be a powerful improvement to make them comfortable using the Hub, which can then bring better results for the Company, even as good or better than Cluster 4. "Less Active" was established for Cluster 3 as the last online purchase made by these customers was last year (see *Appendix 18*). They are a price cautious segment as they present the lowest maximum price per unit, thus, they do occasional purchases. Lastly, Cluster 4, despite including a low number of customers, was considered as "Heavy Volume" as each of them orders huge quantities. Also, they demonstrate high frequency and low recency (meaning,

actively and constantly buying). They might be less sensitive to changes in prices as the minimum, average, and maximum price per unit present a wider amplitude (from 0,8 to 1,6 euros/kg), compared to the other segments, therefore, it can turn into a more valuable cluster.

5. RECOMMENDATIONS

As mentioned in the beginning of the paper, there are other **global variables** (as detailed in *Appendix 19*) that were not included in the clustering analysis; however, they must be involved in the dynamic pricing model (meaning, in the algorithm). Some of them, such as demand, supply, customers data, and relational factors were already mentioned in the Literature Review. Globally speaking, with regards to both online and offline channels, one of them is competitor data (such as substitute products) with the aim of comparing prices between competitors. This way, the algorithm can automatically apply price reductions or upcharges, depending on what the other companies are charging, at a specific moment. Also, raw material market prices should be considered as they are influenced by economic, political and market volatility and will impact production costs. Therefore, when looking at The Navigator Company, a major player in the paper & pulp industry, it should investigate energy and pulp price variations and indexes, as well as inflation rate and currency exchange. Thus, as discussed internally with the Company, their prices are influenced and/or correlated with these variables. Accordingly, when the costs of these raw materials increase, the product price will also increase.

When it comes to exclusively online channels, additional transaction information must also be considered in the algorithm, for instance, product page views in digital platforms. A specific

software that can track all these variables will support the retention of customers, by allowing seamless and continuous contact, including offers and discounts.

6. CONCLUSION

Considering clusters as a future variable/input for the dynamic pricing model could result in higher levels of profit for the Company. There are two main possibilities when changing the final price per unit: slightly increase it for Clusters 2 and 4 and/or slightly decrease it for Clusters 1 and 3. On the one hand, the first option will make a huge difference in revenues, especially in Cluster 4 (due to the huge volume). Also, it might not make such a difference/impact on these clients, thus, they will continue to purchase anyway. On the other hand, the decline in unit price might be compensated by the rise explained above and, it can attract more customers or make the current ones more active in the portal and, thus, increasing the number of orders in the long-term. It is worth to mention that, in Cluster 1, it is better not to take the risk (price above) as it is very diverse, possibly leading to different client's reactions. One of the main limitations of the study was the information that was lost when preparing the SPSS file, transforming data per order into data per client. However, variables were carefully chosen leading to an accurate final output. Additionally, future research could be explored in developing and testing all the other variables. To conclude, clusters were my main contribution to the Company, also suggesting other global variables to be put in place in the future model and an overall roadmap to guide the project, as built through a Gantt chart, a Datamart flow and a Business Requirement (please see them detailed in *Appendixes 20, 21 and 22*).

7. REFERENCES

Baldwin, Grace. 2019. “The History of Dynamic Pricing in 7 Minutes (Or Less).” *Omnia Price Points*. [The History of Dynamic Pricing in 7 Minutes \(Or Less\) \(omniaetail.com\)](https://omniaetail.com)

Bank, Eric. 2022. “What Is a Commodity-Based Industry?” *CHRON*.
[Analysis of the Confectionery Industry \(chron.com\)](https://chron.com)

BenMark, Gadi; Klapdor, Sebastian; Kullmann, Mathias; Sundararajan, Ramji. 2017. “How retailers can drive profitable growth through dynamic pricing.” *McKinsey & Company*.
[How retailers can drive profitable growth through dynamic pricing | McKinsey](https://www.mckinsey.com)

Berg, Peter; Lingqvist, Oskar. 2019. “Pulp, paper, and packaging in the next decade: Transformational change.” *McKinsey & Company*.
[The packaging, pulp and paper industry in the next decade | McKinsey](https://www.mckinsey.com)

Bilgin, Doga; Ellwanger, Reinhard. 2017. “A Dynamic Factor Model for Commodity Prices.” *Bank of Canada*. [A Dynamic Factor Model for Commodity Prices \(bankofcanada.ca\)](https://www.bankofcanada.ca)

Biscontini, Tyler. 2020. “Dynamic pricing (surge pricing).” *Salem Press Encyclopedia*.
[Dynamic pricing \(surge pricing\). - EBSCO](https://www.ebsco.com)

Burns, David; Schottland, David. 2018. “The Formula for Better Pricing in Chemicals.” *Bain & Company*.

Cornish, Rosie. 2017. “Cluster Analysis.” *Mathematics Learning Support Centre*.

Dearth, Brian. 2022. “Dynamic Pricing in Ecommerce: How it Works.” *Vaimo*.
[Dynamic Pricing in Ecommerce: How it Works \(vaimo.com\)](https://vaimo.com)

Dilmegani, Cem. 2022. “Dynamic Pricing in e-Commerce: Implementation & Examples.” *AI Multiple*. [Dynamic Pricing in e-Commerce: Implementation & Examples \(aimultiple.com\)](https://aimultiple.com/dynamic-pricing-in-e-commerce-implementation-examples/)

Dilmegani, Cem. 2022. “Dynamic Pricing: How Does It Work & How to Implement It.” *AI Multiple*. [Dynamic Pricing: How Does It Work & How to Implement It \(aimultiple.com\)](https://aimultiple.com/dynamic-pricing-how-does-it-work-how-to-implement-it/)

Enache, Maria Cristina. 2021. “Machine Learning for Dynamic Pricing in e-Commerce.” *Annals of Dunarea de Jos University*. [Enache.pdf \(ugal.ro\)](https://ugal.ro/enache.pdf)

Goli, Fatemeh; Haghighinasab, Manijeh. 2021. “Dynamic Pricing: A Bibliometric Approach.” *Iranian Journal of Management Studies*. [Dynamic Pricing: A Bibliometric Approach. - EBSCO](https://www.ebsco.com/iranian-journal-of-management-studies/dynamic-pricing-a-bibliometric-approach)

Gupta, Shashank. 2022. “Customer Segmentation using Hierarchical Clustering.” *Enjoy algorithms*. [Customer Segmentation using Hierarchical Clustering \(enjoyalgorithms.com\)](https://enjoyalgorithms.com/customer-segmentation-using-hierarchical-clustering/)

Hassan, Masudul. 2020. “Supply Affecting Variables or Supply Determinants.” *Agribusiness Education & Research International*.

[Supply Affecting Variables or Supply Determinants - Agribusiness Education and Research International](https://www.agribusinesseducationandresearchinternational.com/supply-affecting-variables-or-supply-determinants)

Joshi, Shreya. 2022. “What is Clustering in Machine Learning: Types and Methods.” *Analytixlabs*. [Types of Clustering Algorithms in Machine Learning With Examples \(analytixlabs.co.in\)](https://analytixlabs.co.in/types-of-clustering-algorithms-in-machine-learning-with-examples)

Ke, Jiannan; Zhang, Dan; Zheng, Huan. 2019. “An Approximate Dynamic Programming Approach to Dynamic Pricing for Network Revenue Management.” *Production & Operations Management*.

[An Approximate Dynamic Programming Approach to Dynamic Pricing for Network Revenue Management. - EBSCO](#)

Morenne, Benoît. 2022. “U.S. Gasoline Prices Are Climbing Again, Pressuring Consumers.” *The Wall Street Journal*. [U.S. Gasoline Prices Are Climbing Again, Pressuring Consumers - WSJ](#)

Nidhi. 2022. “Dynamic Pricing for Petrochemicals.” *Tech Mahindra*.

[PowerPoint Presentation \(techmahindra.com\)](#)

Phillips, Robert. 2021. *Pricing and Revenue Optimization: Second Edition*. California: Stanford Business Books.

Pudi, Kiran. 2022. “Seven Design Decisions to Consider when Developing B2B Dynamic Pricing Engines.” *Simon Kucher & Partners*.

[B2B Dynamic Pricing: 7 Design Decisions to Consider \(simon-kucher.com\)](#)

Ramesh, Shashank Markapuram. 2021. “How dynamic pricing works: data driven price optimization.” *7Learnings*.

[How dynamic pricing works: data driven price optimization \(7learnings.com\)](#)

Sohail, Shairoz. 2018. “A Comprehensive Introduction to Clustering Methods.” *Medium*.

[A Comprehensive Introduction to Clustering Methods | by Shairoz Sohail | Medium](#)

Thornhill, John. 2022. “Algorithmic pricing is both efficient and absurd.” *Financial Times*.

[Algorithmic pricing is both efficient and absurd | Financial Times \(ft.com\)](#)

Vasishtha, Garima. 2022. “Commodity price cycles: Causes and consequences.” *World Bank*

Blogs. [Commodity price cycles: Causes and consequences \(worldbank.org\)](#)

Vouk, Ira. 2018. “2 Types of Data Needed for Successful Dynamic Pricing.” *Hospitalitynet*.

[2 Types of Data Needed for Successful Dynamic Pricing | By Ira Vouk \(hospitalitynet.org\)](#)

Wells, Taylor. 2020. “The Latest Dynamic Pricing Model Example For B2B Firms.” *Taylor*

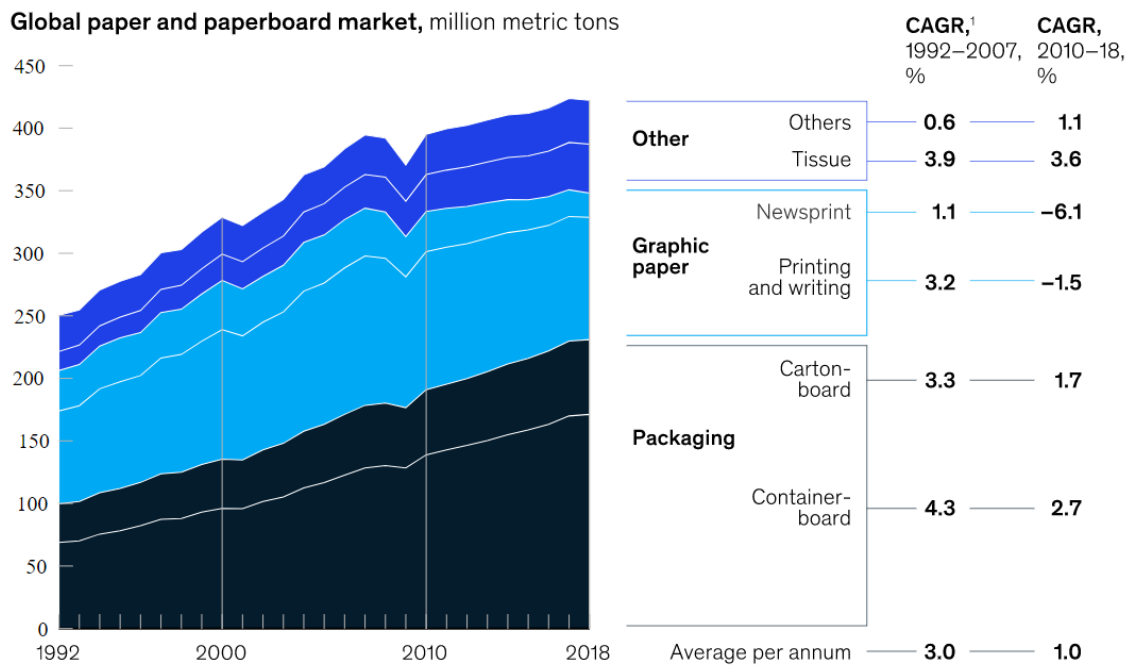
Wells. [Latest Dynamic Pricing Model Example For B2B Firms !\[\]\(986082884a323475ef59af56b5554821_img.jpg\) \(taylorwells.com.au\)](#)

Zhang, Jonathan; Netzer, Oded; Ansari, Asim. 2014. “Dynamic Targeted Pricing in B2B

Relationships.” *JSTOR Journals*. [Dynamic Targeted Pricing in B2B Relationships - EBSCO](#)

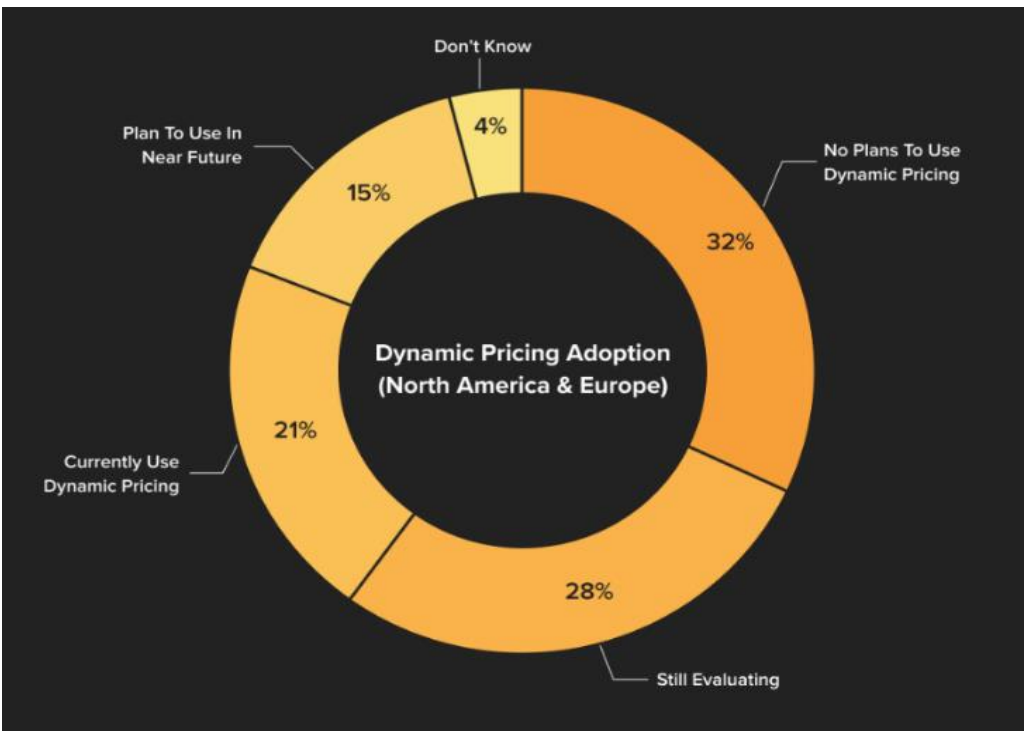
8. APPENDICES

Exhibit 1 – Global paper and paperboard market, million metric tons



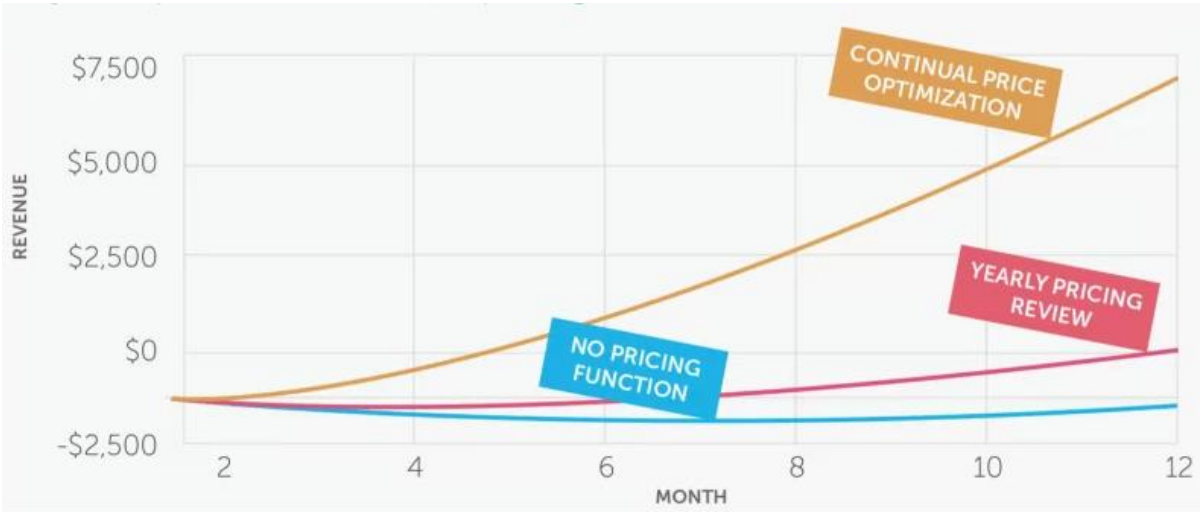
Source: Resource Information Systems Inc (RISI), February 2019

Exhibit 2 – Dynamic Pricing in E-commerce



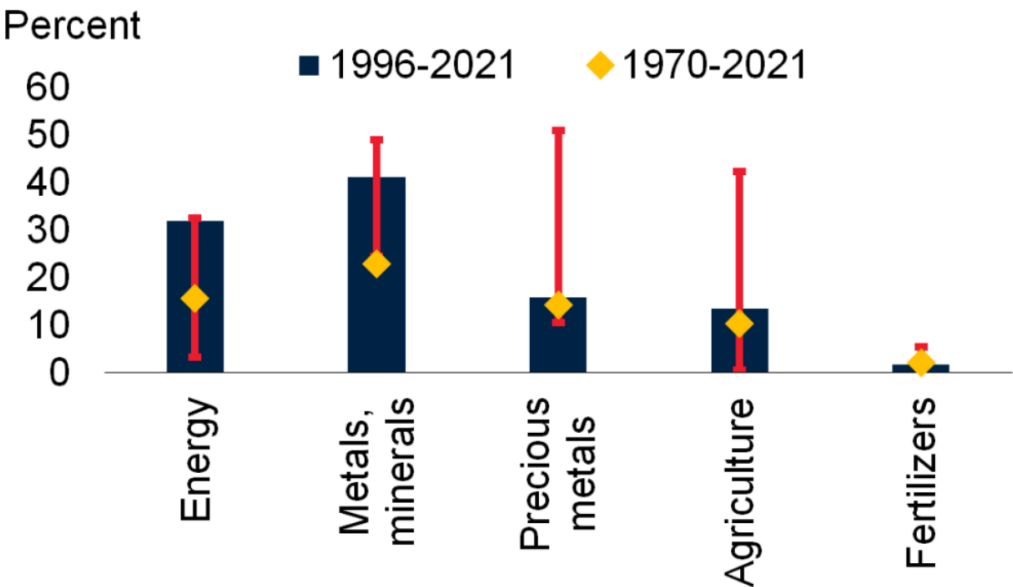
Source: SearchNode (Nosto)

Exhibit 3 – Payback periods for different pricing commitments



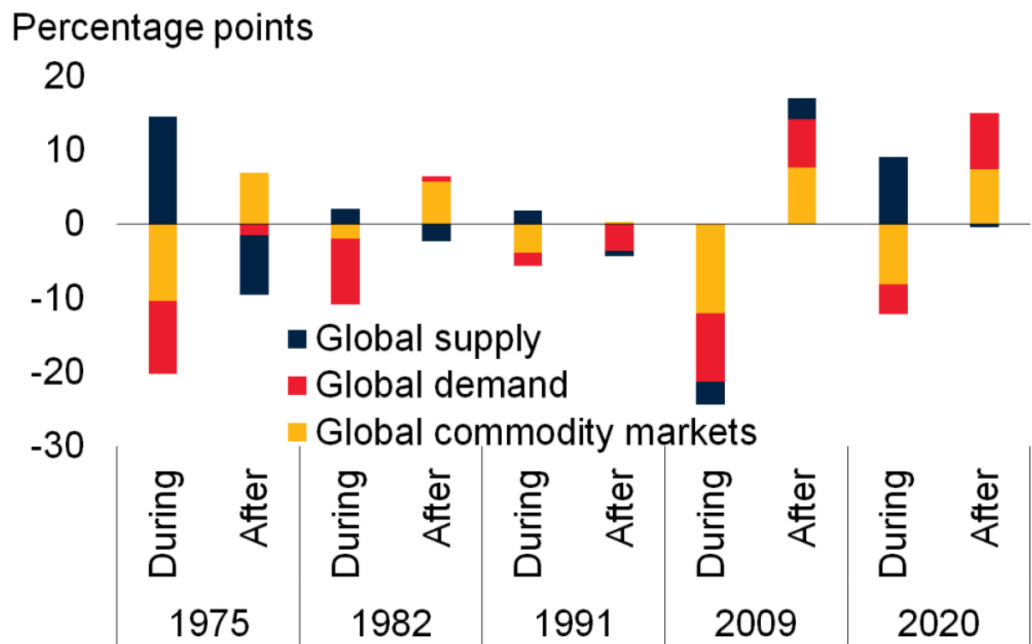
Source: Price Intelligently

Exhibit 4 - Commodity price variation due to the global factor, 1970-2021 and 1996-2021



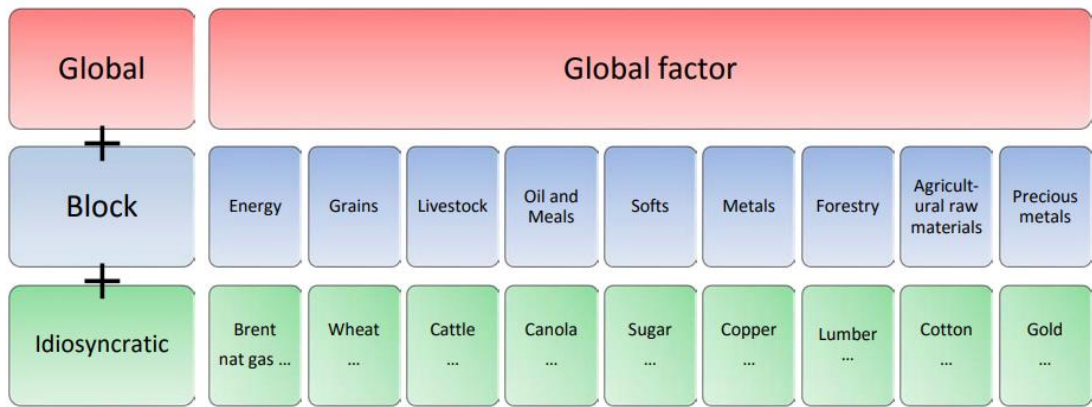
Source: Baumeister and Hamilton (2019); Ha, Kose, and Ohnsorge (2021); Kabundi and Zahid (Forthcoming); World Bank.

Exhibit 5 - Contributions of global shocks to the variation in global commodity prices around recessions and slowdowns



Source: Baumeister and Hamilton (2019); Ha, Kose, and Ohnsorge (2021); Kabundi and Zahid (Forthcoming); World Bank.

Exhibit 6 – Model Block Structure



Source: <https://www.bankofcanada.ca/wp-content/uploads/2017/09/san2017-12.pdf>

Exhibit 7 – Clients used for clustering

Clients' names		
A UM A.ALVES AL BAIDAA ALB.R.N. ALVES-IND T ALMACEN C. PAPELERIA ALMACENES CAYPE ALMACENES IRIGARAY ALMEIDA & NEVES ALTOINFOR AMBAR AMERICANA -PAPELARIA ANTONIO R. MOTA ARGA VALLADOLID ARPON PAPELES ARTE-CAD ARTEPAPEL S.A. AVANSAS AVILA TECNIPAPEL BARBERO PIETRO BERNI BERTO PASQUALE SRL BIAGINI BLANCAFORT 2000 BOBIRAL CANARIA MAT.OFICINA CANON BULGARIA CARLIBUR CARLINGAL CARTISA CBI DIFFUSION CENTRO UFFICIO CGITI CHIMNIAR CLERRE UFFICIO CISCRA CLIPOURO COMALPA COMERCIAL DEL SUR COMERCIAL DON PAPEL COMUNICA CONTISYSTEMS CONTOR COPIDATA CORSINI CORVALL CTT CUSTODIO CABIDO DE SALABERT DESCOM DESSAUVAGE DISEÑOS Y APLIC DISTRI MAICAR DOBEL DUE UFFICIO E. HUBER ECOFLOAT ED. SALVAT EDICIONES WIKINGO EDITORIAL BRUÑO EKAI EL SECRETARIO ELKAR EMA LTD EMBA EMERSON POLSKA EMIN KAGITCILIK ESCALA PAPELERIA EURO TOIMISTOTUKUT EXERTIS FIRMO FOLDER	FORCESA FORMATO FULVIO NAVARRO E HIJ GECAL GIL SOTO GLOBAL PAPER GRAFO GRAFOPLAS GS OFIMATICA GUERRO PAPELERIAS HÄMEEN HERMANOS CEBRIAN HITCO HOVAT ICR IGEPA CARTACELL IGEPA PLANA IGEPA POLSKA IMEDISA IMPRESA INFOTARK INGROS CARTA J. H. ORNELAS JB COMERCIO GLOBAL JORGE FERNANDES JOSE BORDA J-QUELHAS KAENGURUH KUVERT KIRJAPAINO LA CONTABILE LAPIN LIBER DIGITAL LIBRA VITALIS LTD LINDENMEYR (UK) LOGIMADE LUDONA MAESPA MAKRO PAPER MALAK STATIONERY MANIPULADOS CANADA MARTIN BALMES MATA SUMINISTROS MERCADO DE PAPEL MERCAPEL MIMBEK MOAR SRL MONDOFFICE MONTTE MOURAPLÁS MYO NOVAKOPA NUCO OFFICART OFFICE AUTHORITY OFFICE24 OFFICEDAY LATVIA OFISANTEC OFISUR OFITURIA 3000 OLMAR OMNI SERVIS ORAF OY EKMAN PALMIGRAFICA PAPELERA CRISTÓBAL PAPELERIA SENA PAPELES NAVARRO PAPELNOR PAPER PLANET PBS CONNECT PMC GRUP 1985	POLAP POLYCOPY PAPER PRIMA PRODOUT PRONTOPACK PUCHADES RAMON GARCIA REDOFFICE REDPAPEL RIMPEKS ROCLAYER ROMANI ROSSIGNOL ROTAGRAMA ROTGER RUI & FERREIRA RUMOR SEABRA TAVARES SERVINFORM SET PRAT SHAHAR SLAVEY.91 SOLUCIONES GRAFIQUES SPAGGIARI SPRINGFIELD BUSINES STEINMETZ SUMINISTROS SURPAPEL SYSTEEMA TEE-HOO TELE MAIL TIPOGRAFIA PRICOS TOMPLA TOPTONER UAB "SANITEX" UNION PAPELERA RODE VADELO VISIPAPEL WJ BUSINESS PARTNER WZ EUROCOPERT

Exhibit 8 – Detail of some of the variables (micro data) provided by the Company

Market code	Market name
10	PORTUGAL
11	SPAIN
12	FRANCE
13	GERMANY
16	TURKEY
17	UK
22	BELGIUM
23	THE NETHERLANDS
24	ITALY
26	BALKANS
92L	LATIN AMERICA SPOT
92M	MIDDLE EAST
93A	POLAND
94	NORTHERN EUROPE & BALTICS

Group code	Group name
BPG	BPGI
CAN	CANON
CR8	CORAL GROUP PURCHASING CONSORTIUM
IGE	IGEPA
NOA	NORDIC OFFICE ALLIANCE
NOK	NOVAKOPA
ODY	OFFICEDAY
RAJ	RAJA
TOM	TOMPLA

Customer type code	Customer type name
ECV	CONVERTERS
EOT	OTHERS
EPH	PRINTERS AND PUBLISHERS
OEM	ORIGINAL EQUIPMENT MANUFACTURER
OSB	BUYINGGROUPS
OSC	CONTRACTSTATIONERS
OSM	MAILORDER
OSR	OSD-RETAILERS
OSW	OSD-WHOLESALERS
OTH	OTHER
PKB	PACKAGING CONVERTERS BAGS
PKE	PACKAGING EXTRUSION/COATING
PKF	PACKAGING CONVERTERS FOOD
PPM	PAPER MERCHANTS
RET	RETAILER
TRD	TRADING COMPANY

Brand group
BUSINESS PAPER CANON CONNECT COPIER PAPER COPY & PRINT DISCOVERY DISNAK EMERSON ENVIROCOPY EVERYDAY COPY EXPLORER FAST MAIL FEGOL GKRAFT GLOBAL GLOBULUS GREEN INACOPIA INASET LASER COPY MULTIOFFICE MY PRINT NAVIGATOR NEUTRAL NORDIC OFFICE OFFICE PAPER OFFICE STANDARD OFFSET PREMIUM OFFSET STANDARD OFFSET ZAFIRO PIONEER SOPORSET SPEED OFFICE PAPER STANDARD TARGET TESCO THE DAY COPY TREND KARNAK WHITE OFFICE PAPER WILKO WINNER

Brand name		
BUSINESS PAPER CANON BLACK LABEL OFFICE PEFC CONNECT COPIER PAPER COPY & PRINT DISCOVERY FSC CERTIFIED DISCOVERY FSC CERTIFIED 2 HOLE DISNAK EDUCATIONAL PAPER FSC CERTIFIED EMERSON MAXX WHITE PEFC ENVIROCOPY PEFC EVERYDAY COPY EVERYDAY COPY PEFC EXPLORER ICOLOUR FSC CERTIFIED EXPLORER IDEFINITION FSC CERTIFIED	LASER COPY MULTIOFFICE 4H PEFC MULTIOFFICE PEFC MY PRINT MY PRINT PEFC NAVIGATOR 625 NAVIGATOR ADVANCED FSC CERTIFIED NAVIGATOR BOLD DESIGN FSC CERTIFIED NAVIGATOR CLR UHD FSC CERTIFIED NAVIGATOR ECO FSC CERTIFIED NAVIGATOR EXP UHD FSC CERTIFIED NAVIGATOR HARD COVER FSC CERTIFIED NAVIGATOR HOME PACK FSC CERTIFIED NAVIGATOR HOME PACK UHD FSC CERTIFIED NAVIGATOR HOME PACK XS UHD FSC CERTIFIED	OFFSET STANDARD OFFSET PREMIUM 161 FSC CERTIFIED OFFSET ZAFIRO PIONEER DISTINCT FSC CERTIFIED PIONEER EXCLUSIVE FSC CERTIFIED PIONEER FRESH FSC CERTIFIED PIONEER OFFSET PIONEER OUTSTANDING FSC CERTIFIED PIONEER PERFECT FSC CERTIFIED PIONEER SHI ZEN FSC CERTIFIED PIONEER SPECIAL FSC CERTIFIED SOPORSET OFFSET SOPORSET PREMIUM OFFSET SOPORSET PREMIUM OFFSET FSC CERTIFIED

EXPLORER IPERFORMANCE FSC CERTIFIED	NAVIGATOR HYB FSC CERTIFIED	SOPORSET PREMIUM OFFSET PEFC
EXPLORER IQUALITY FSC CERTIFIED	NAVIGATOR OFC FSC CERTIFIED	SOPORSET PREMIUM PREPRINT FSC CERTIFIED
EXPLORER OFFSET	NAVIGATOR P2 UHD FSC CERTIFIED	SOPORSET PREPRT
EXPLORER OFFSET FSC CERTIFIED	NAVIGATOR P4 UHD FSC CERTIFIED	SPEED OFFICE PAPER
FASTMAILPREMIUM	NAVIGATOR PLAT	STANDARD
FASTMAILPREMIUM FSC CERTIFIED	NAVIGATOR PLATINUM FSC CERTIFIED	TARGET CORPORATE PEFC
FASTMAILPREMIUM PEFC	NAVIGATOR PLATINUM UHD FSC CERTIFIED	TARGET EXECUTIVE FSC CERTIFIED
FEGOL 360°	NAVIGATOR PRE UHD FSC CERTIFIED	TARGET PROFESSIONAL 2H PEFC
FEGOL PLUS PEFC	NAVIGATOR PREMIUM ENVELOPES	TARGET PROFESSIONAL FSC CERTIFIED
FEGOL XPRESS	NAVIGATOR PREMIUM ENVELOPES FSC CERTIFIE	TARGET PROFESSIONAL PEFC
GKRAFT BAG	NAVIGATOR PREMIUM ENVELOPES PEFC	TARGET PROFESSIONAL SG PEFC
GKRAFT BAG FSC CERTIFIED	NAVIGATOR PREMIUM INKJET	TESCO BASICS PEFC
GKRAFT BAG PEFC	NAVIGATOR PREMIUM WRITING FSC CERTIFIED	TESCO MULTIPURPOSE PEFC
GKRAFT FLEX	NAVIGATOR PREPRINT	TESCO NEUTRAL PEFC
GKRAFT FLEX FSC CERTIFIED	NAVIGATOR STUDENTS 2020	TESCO PRINTER PAPER PEFC
GKRAFT FLEX PEFC	NAVIGATOR UNI UHD 2022 FSC CERTIFIED	THE DAY COPY PEFC
GLOBAL	NAVIGATOR UNI UHD CO2N FSC CERTIFIED	TREND KARNAK PEFC
GLOBULUS STANDARD	NAVIGATOR UNI UHD FSC CERTIFIED	WHITE KRAFT FSC CERTIFIED
GREEN PEFC	NEUTRAL	WHITE OFFICE PAPER
INACOPIA COLOUR FSC CERTIFIED	NEUTRO 75G	WILKO COPIER PAPER PEFC
INACOPIA ELITE FSC CERTIFIED	NORDIC OFFICE PEFC	WINNER
INACOPIA OFFICE FSC CERTIFIED	OFFICE PAPER	
INACOPIA OFFICE PEFC	OFFICE PAPER 80	
INASET PLUS DIGITAL	OFFICE PAPER EXCELLENT PERFORMANCE	
INASET PLUS LASER	OFFICE PAPER P	
INASET PLUS LASER FSC CERTIFIED	OFFICE PREMIUM 169	
INASET PLUS OFFSET	OFFICE PREMIUM 169 FSC CERTIFIED	
INASET PLUS OFFSET FSC CERTIFIED	OFFICE PREMIUM 169 PEFC CERTIFIED	
INASET PLUS OFFSET PEFC	OFFICE STANDARD	
LASER COPY	OFFSET PREMIUM	
MULTIOFFICE 4H PEFC	OFFSET PREMIUM 161	

Exhibit 9 – Coefficient of importance (%) attributed for each variable

Importance level
High
Medium
Low

General Variable	Variable name	Importance level	Total percentage	Individual percentage
Orders	Number of orders	Low	6%	6%
Product format (Q)	Cutsize	Medium	9%	3%
	Folio			3%
	Reels			3%
Strategic Brand (Q)	Col's	High	27%	9%
	Mill Brands			9%
	Mill Wrappers			9%
Grade (Q)	Economic	High	27%	9%
	Standard			9%
	Premium			9%
Quantity & Price	Average Quantity per order	Medium	25%	4%
	Maximum unit price	High		5%
	Minimum unit price	High		5%
	Average unit price	Medium		4%
	Total amount paid	Low		3%
	Average amount paid per order	Medium		4%
Purchase Date	Number of days since last purchase	Medium	6%	6%

Exhibit 10 – Dendrogram from IBM SPSS

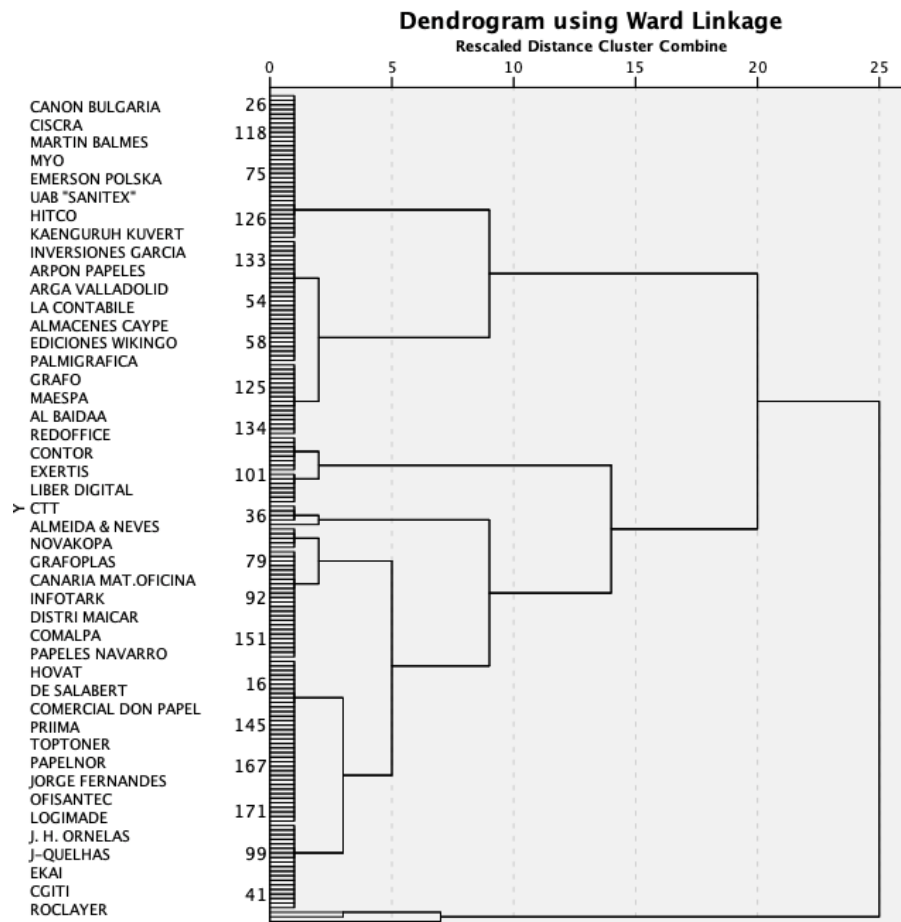
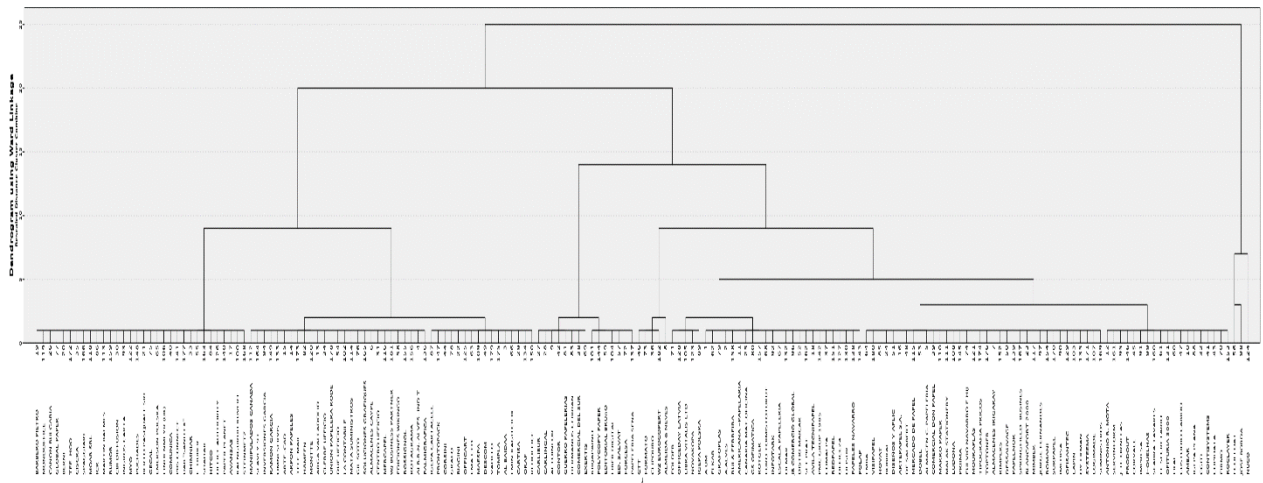


Exhibit 11 – Clusters composition

Cluster	Clients' names
Cluster 1	A UM, A.ALVES, ALMACEN C. PAPELERIA, ALMACENES IRIGARAY, ALMEIDA & NEVES, AMBAR, AMERICANA -PAPELARIA, ANTONIO R. MOTA, ARTEPAPEL S.A., AVILA TECNIPAPEL, BLANCAFORT 2000, BOBIRAL, CANARIA MAT.OFICINA, CGITI, CLIPOURO, COMALPA, COMERCIAL DON PAPEL, CONTISYSTEMS, COPIDATA, CORVALL, CTT, CUSTODIO CABIDO, DE SALABERT, DESSAUVAGE, DISEÑOS Y APLIC, DISTRI MAICAR, DOBEL, EKAI, EL SECRETARIO, ELKAR, EMBA, ESCALA PAPELERIA, EURO TOIMISTOTUKUT, FIRMO, FOLDER, FORMATO, FULVIO NAVARRO E HIJ, GRAFOPLAS, GS OFIMATICA, HOVAT, IGEPa PLANA, IGEPa POLSKA, IMEDISA, IMPRESA, INFOTARK, J. H. ORNELAS, JB COMERCIO GLOBAL, JORGE FERNANDES, J-QUELHAS, LAPIN, LIBRA VITALIS LTD, LOGIMADE, LUDONA, MAKRO PAPER, MALAK STATIONERY, MERCADO DE PAPEL, MIMBEK, MOURAPLÁS, NOVAKOPA, OFFICE24, OFFICEDAY LATVIA, OFISANTEC, OFISUR, OFITURIA 3000, OLMAR, OY EKMAN, PAPELES NAVARRO, PAPELNOR, PMC GRUP 1985, POLAP, PRIIMA, PRODOUT, REDPAPEL, RIMPEKS, ROCLAYER, ROMANI, ROTGER, RUI & FERREIRA, SEABRA TAVARES, SERVINFORM, SET PRAT, SPRINGFIELD BUSINES, SUMINISTROS, SURPAPEL, SYSTEEMA, TIPOGRAFIA PRICOS, TOPTONER, VISIPAPEL, WZ EUROCOPERT
Cluster 2	AL BAIIDAA, ALB.R.N. ALVES-IND T, ALMACENES CAYPE, ARG VALLADOLID, ARPON PAPELES, ARTE-CAD, AVANSAS, BARBERO PIETRO, BERNI, BERTO PASQUALE SRL, BIAGINI, CANON BULGARIA, CARTISA, CBI DIFFUSION, CENTRO UFFICIO, CHIMNIAR, CIERRE UFFICIO, CISCRA, COMUNICA, CORSINI, DESCOM, DUE UFFICIO, E. HUBER, EDICIONES, WIKINGO, EMA LTD, EMERSON POLSKA, EMIN KAGITCILIK, GECAL, GIL SOTO, GLOBAL PAPER, GRAFO, HÄMEEN, HITCO, ICR, IGEPa CARTACELL, INGROS CARTA, INVERSIONES GARCIA, KAENGURUH KUVERT, LA CONTABILE, LINDENMEYR (UK), MAESPA, MANIPULADOS CANADA, MARTIN BALMES, MATA SUMINISTROS, MERCAPEL, MOAR SRL, MONDOFFICE, MONTTE, MYO, OFFICART, OFFICE AUTHORITY, OMNI SERVIS, ORAF, PALMIGRAFICA. PAPER PLANET, PBS CONNECT, PRONTOPACK, PUCHADES, RAMON GARCIA, REDOFFICE, ROSSIGNOL, ROTAGRAMA, RUMOR, SHAHAR, SLAVEY.91, SOLUCIONES GRAFIQUES, SPAGGIARI, STEINMETZ, TEE-HOO, TELE MAIL, TOMPLA, UAB "SANITEX", UNION PAPELERA RODE, VADELO, WJ BUSINESS PARTNER
Cluster 3	ALTOINFOR, CARLIBUR, CARLINGAL, COMERCIAL DEL SUR, CONTOR, ED. SALVAT, EDITORIAL BRUÑO, EXERTIS, FORCESA, GUERRO PAPELERIAS, HERMANOS CEBRIAN, KIRJAPAINO, LIBER DIGITAL, PAPELERIA SENA, POLYCOPY PAPER
Cluster 4	ECOFLOAT, JOSE BORDA, NUCO

Exhibit 12 – Data regarding Quantity variable

Clusters	Average Q of Mill Brands	Average Q of Mill Wrappers	Average Q of Col's	Average Q of Premium	Average Q of Standard	Average Q of Economy
1	298 121,8	67 189,1	5 628,2	251 874,6	98 744,6	20 320,0
2	96 127,6	16 513,4	3 819,5	78 264,1	38 196,4	0,0
3	20 882,6	11 570,9	2 981,8	24 695,2	3 617,2	7 122,9
4	2 954 506,3	580 092,7	1 731 791,7	2 135 493,7	2 389 039,0	741 858,0
Total	235 819,6	50 176,8	33 118,0	192 656,9	103 705,3	22 752,2

Exhibit 13 – Data regarding Price variable

Clusters	Average of Total amount paid	Average of Average amount paid per order
1	419 020,4	9 657,7
2	153 927,7	18 385,3
3	32 743,3	8 439,3
4	5 793 472,0	17 332,8
Total	366 532,8	13 280,3

Exhibit 14 – Seasonality characterization

Clusters	Average of Month when clients spend more
1	7,2
2	8,5
3	6,0
4	7,3
Total average	7,6

Exhibit 15 – Market characterization

Market	Cluster 1	Cluster 1 %	Cluster 2	Cluster 2 %	Cluster 3	Cluster 3 %	Cluster 4	Cluster 4 %
BALKANS	1	1%	4	5%	0	0%	0	0%
BELGIUM	1	1%	0	0%	0	0%	0	0%
FRANCE	0	0%	1	1%	0	0%	0	0%
GERMANY	0	0%	2	3%	0	0%	0	0%
ITALY	0	0%	21	28%	0	0%	0	0%
LATIN AMERICA SPOT	0	0%	3	4%	0	0%	0	0%
MIDDLE EAST	1	1%	6	8%	0	0%	0	0%
NORTHERN EUROPE & BALTICS	12	13%	5	7%	2	13%	0	0%
POLAND	2	2%	2	3%	0	0%	0	0%
PORTUGAL	30	34%	2	3%	1	7%	2	67%
SPAIN	40	45%	24	32%	10	67%	0	0%
THE NETHERLANDS	0	0%	2	3%	0	0%	0	0%
TURKEY	0	0%	2	3%	0	0%	0	0%
UK	2	2%	1	1%	2	13%	1	33%
Total	89	100%	75	100%	15	100%	3	100%

Exhibit 15.1 – Market characterization

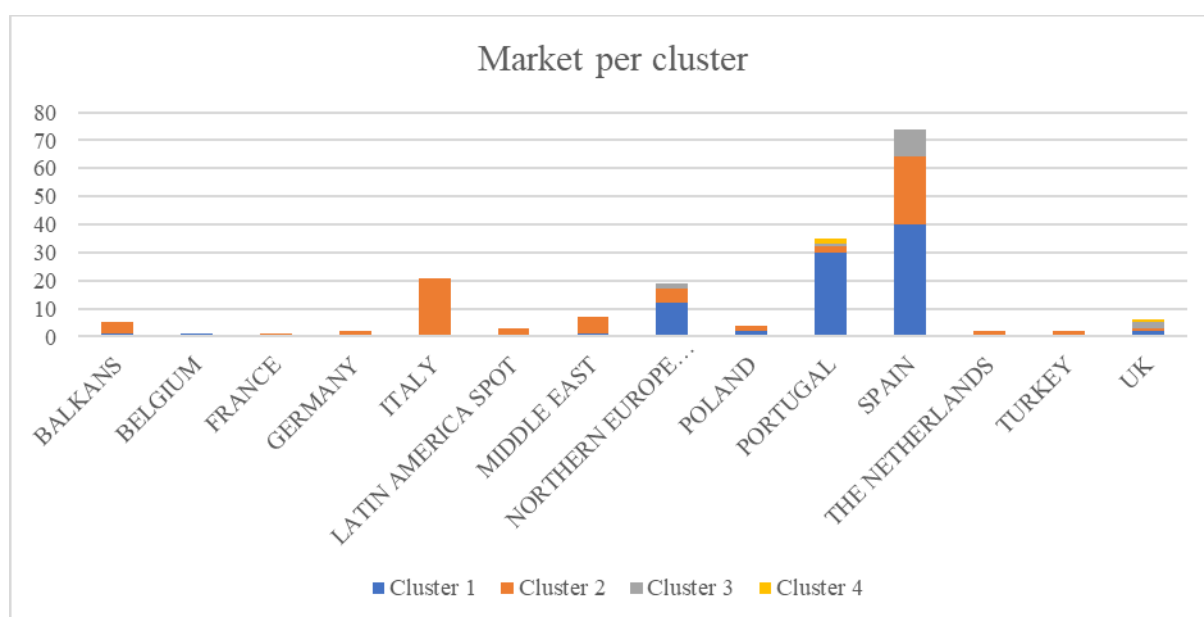


Exhibit 16 – Customer type characterization

Customer type	Customer type	Cluster 1	Cluster 1 %	Cluster 2	Cluster 2 %	Cluster 3	Cluster 3 %	Cluster 4	Cluster 4 %
CONVERTERS	ECV	7	8%	6	8%	1	7%	1	33%
OTHERS	EOT	0	0%	2	3%	0	0%	0	0%
PRINTERS AND PUBLISHERS	EPH	8	9%	7	9%	4	27%	0	0%
ORIGINAL EQUIPMENT MANUFACTURER	OEM	0	0%	1	1%	0	0%	0	0%
BUYINGGROUPS	OSB	1	1%	1	1%	0	0%	0	0%
CONTRACTSTATIONERS	OSC	19	21%	10	13%	4	27%	0	0%
MAILORDER	OSM	0	0%	1	1%	0	0%	0	0%
OSD-RETAILERS	OSR	3	3%	8	11%	0	0%	1	33%
OSD-WHOLESALEERS	OSW	23	26%	15	20%	4	27%	0	0%
OTHER	OTH	2	2%	5	7%	0	0%	1	33%
PACKAGING CONVERTERS BAGS	PKB	5	6%	0	0%	0	0%	0	0%
PACKAGING EXTRUSION/COATING	PKE	1	1%	0	0%	0	0%	0	0%
PACKAGING CONVERTERS FOOD	PKF	1	1%	0	0%	0	0%	0	0%
PAPER MERCHANTS	PPM	16	18%	18	24%	2	13%	0	0%
RETAILER	RET	3	3%	0	0%	0	0%	0	0%
TRADING COMPANY	TRD		0%	1	1%	0	0%	0	0%
Total		89	100%	75	100%	15	100%	3	100%

Customer type	Number of clients	Percentage
CONVERTERS	15	8%
OTHERS	2	1%
PRINTERS AND PUBLISHERS	19	10%
ORIGINAL EQUIPMENT MANUFACTURER	1	1%
BUYINGGROUPS	2	1%
CONTRACTSTATIONERS	33	18%
MAILORDER	1	1%
OSD-RETAILERS	12	7%
OSD-WHOLESALEERS	42	23%
OTHER	8	4%
PACKAGING CONVERTERS BAGS	5	3%
PACKAGING EXTRUSION/COATING	1	1%
PACKAGING CONVERTERS FOOD	1	1%
PAPER MERCHANTS	36	20%
RETAILER	3	2%
TRADING COMPANY	1	1%
Total	182	100%

Exhibit 16.1 – Customer type characterization

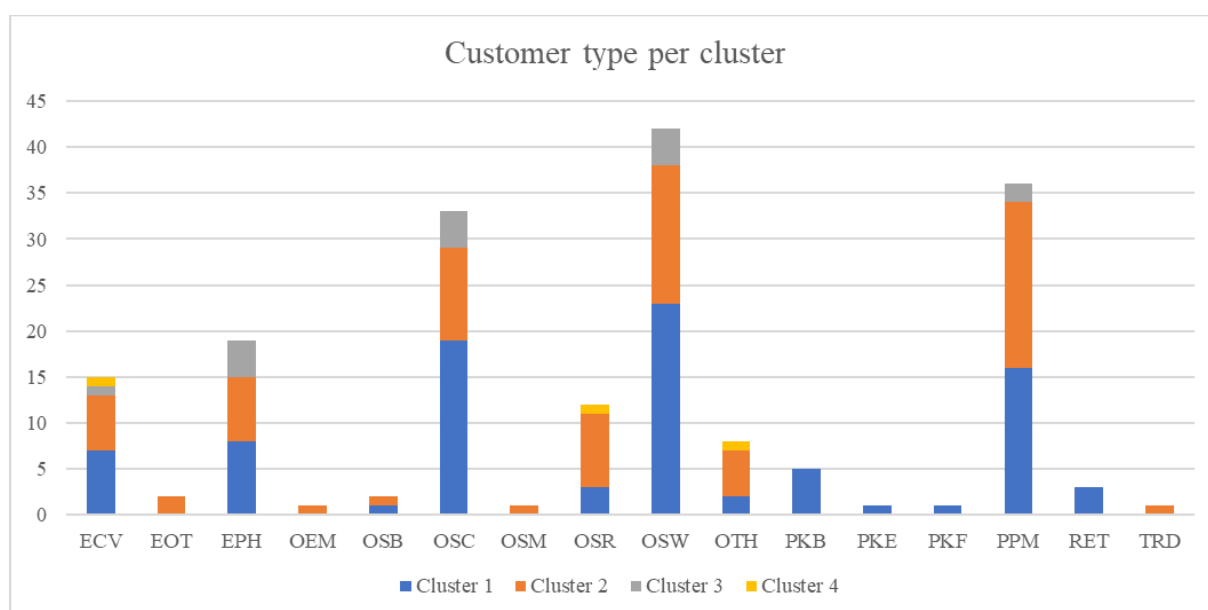


Exhibit 17 – Client group characterization

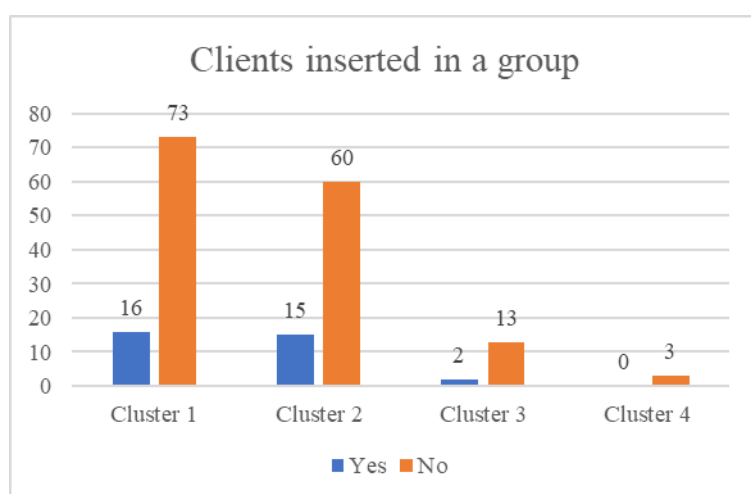


Exhibit 18 – Cluster 3 purchases in the Offline channel

	<i>Online</i>	<i>Offline</i>		
	<i>Mar 2021 - Oct 2022</i>	<i>Mar-Dec 2021</i>	<i>Jan-Oct 2022</i>	
Client name	Nr of days since last purchase	Total Quantity	Total Quantity	% Change
ALTOINFOR	415	2 349 728	2 214 182	-6%
CARLIBUR	470	133 244	109 796	-18%
CARLINGAL	431	0	0	0%
COMERCIAL DEL SUR	309	5 667 493	4 277 435	-25%
CONTOR	257	24 322	0	-100%
ED. SALVAT	555	48 227	68 254	42%
EDITORIAL BRUÑO	551	10 140	104 218	928%
EXERTIS	382	684 587	650 239	-5%
FORCESA	510	638 254	1 176 621	84%
GUERRO PAPELERIAS	246	23 285	25 158	8%
HERMANOS CEBRIAN	269	186 140	363 681	95%
KIRJAPAINO	380	178 230	241 753	36%
LIBER DIGITAL	415	223 132	225 532	1%
PAPELERIA SENA	505	646 695	824 462	27%
POLYCOPY PAPER	338	540 807	527 314	-2%

Cluster 3 was considered “Less Active” in the Online channel. What about their performance in the Offline channel? Comparing ten months of 2022 to 2021, it seems that some clients drop out of the offline channel as well, but other clients are active there. For instance, Carlingal have no offline orders, however, Editorial BRUÑO increased exponentially its quantity bought (offline) from 2021 to 2022.

Furthermore, in **Cluster 4**, composed by only 3 clients, they seem to continue to buy through the offline channel, however, representing a lower volume, when compared to the NVG Hub.

Exhibit 19 – Global variables impacting the Dynamic Pricing Model

Global Variables	Inputs
Economy & Politics	Exchange rates
	Freight index
	Manufacturing confidence (PMI)
	Consumer confidence indexes
	Energy average market price
	GDP
	Labor market (unemployment rate)
	Inflation rate (Consumer Price Index or Producer Price Index)
	Brent spot price
	Stock market price
	One-off events
	Political disruptions (wars --> lack of commodities --> reduction in production)
Industry Market	PIX (Pulp)
	Pipeline Stock levels
	Industry operating rate
	Order lead-time
	Euro Graph/EMGE reports (market capacity, stock days, PIX indexes)
	Loss of market share to foreign competitors
	Reductions/Closures of pulp and paper mills
	Industry order inflow
Competitor Data	Main competitors list
	List and Ship prices
	Geography/Location
	Novelties and Substitute products' prices (including the ones sold by the company and its competitors)
	Catalogue analysis (products available)
	Analysis of supply and stock
	Product reviews/ratings
Supply	Stock levels
	Sales out
	Current and Future production costs
	Agricultural commodity internal availability
	Price expectations
	Means of transportation and communication
	Seller expectations
	Number of sellers
	Improved technology
	Taxation and subsidies
Demand	Government policy and regulations (quotations, tariffs)
	Product seasonality
	Operational status

<i>Additional Transaction Information</i>	Automatized forecast
	Product page views in digital platforms
	Items the customer has viewed
	Items they put in their shopping baskets
	Items they deleted or cancelled from their baskets
	Items they have saved or put on a wish list
	Items they have searched for
Consumer Profile	<u>Segmentation & Data analysis (clustering analysis from IBM SPSS previously presented)</u>
	Orders and Quantities
	Quote Price - RFQ
	Demographic data (age, gender, current location and permanent residence, income)
	Behavioral data (customer's spending habits, channel used, customer's willingness to search for good prices)
	Expectations about price changes
	Number and method of ordering
	Day and time of the day
	Emotional needs and expectations, Satisfaction and Perceived value
	Relationship Quality, Trust and Commitment
	Product packaging/design
	Customer knowledge about the product and Purchase intention

Dyamic Pricing Model impact

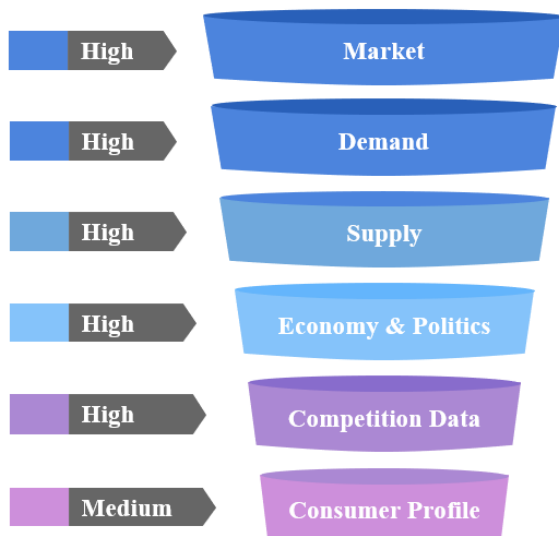


Exhibit 20 – Gantt Chart

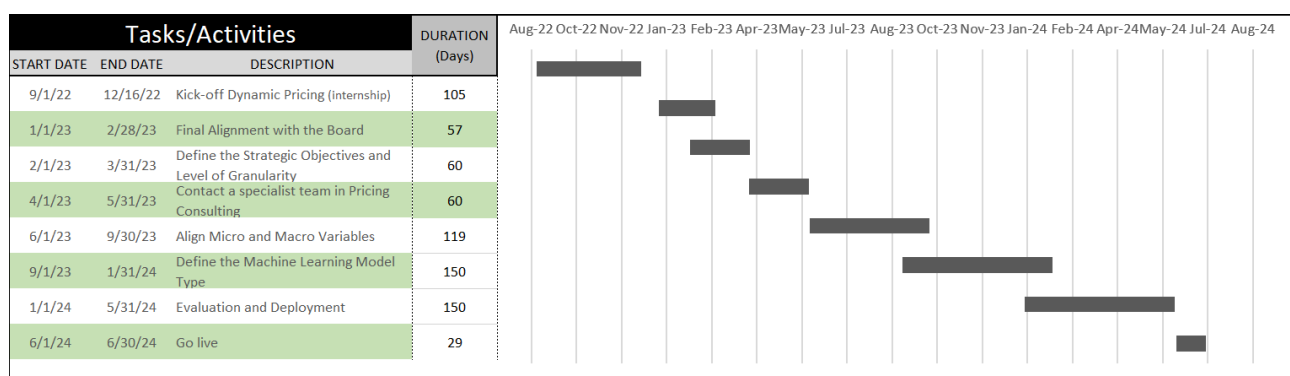


Exhibit 21 – Business Process Flow Diagram (Datamart)

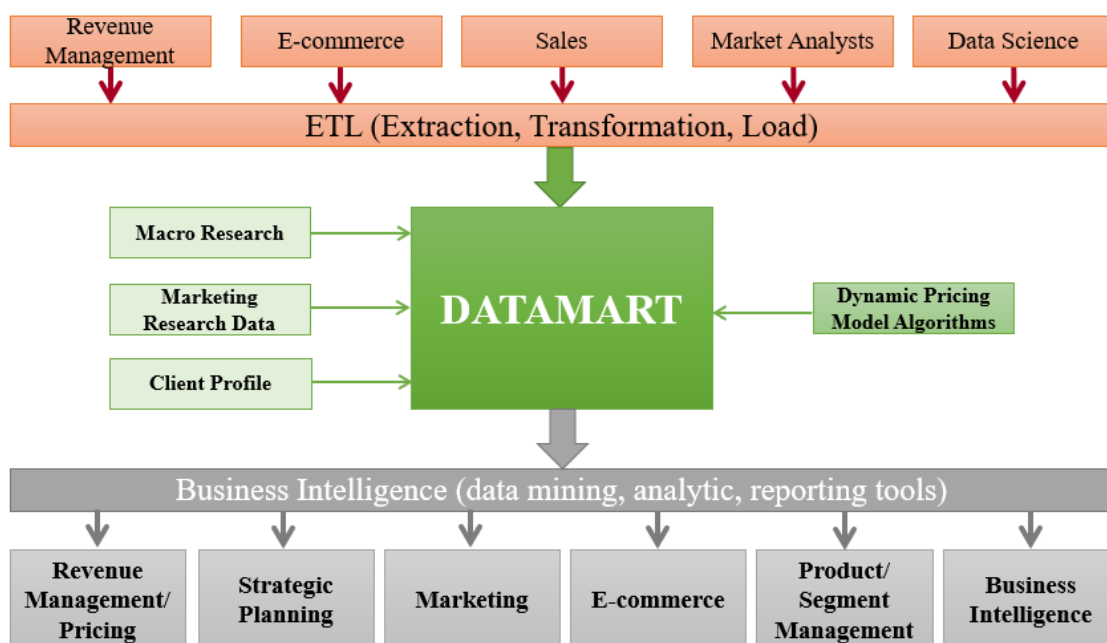


Exhibit 22 – Business Requirement

Please find the attachment to access the Business Requirement for Dynamic Pricing Model:



Business%20Require
ment_Dynamic%20Pr