Determination of factors used to influence purchasing price: Enhancing profitability and competitive edge in discount retail chains

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ABSTRACT

This study investigates the key determinants of purchasing prices in the retail sector, with a focus on Dollarama, a major Canadian discount retailer. Using Ordinary Least Squares (OLS) regression, the research analyzes the influence of four core operational variables: Gross Margin (GM), Minimum Order Quantity (MOQ), stock levels, and consumer demand—on purchasing price. Initial exploratory analysis using scatter plots indicated a strong positive relationship between GM and purchasing price, a negative relationship with demand, and weaker but noticeable trends for stock levels and MOQ.

Diagnostic checks revealed violations of OLS assumptions related to linearity and constant variance. To address these issues, a logarithmic transformation was applied to both dependent and independent variables. Post-transformation, the model satisfied all key assumptions, enhancing the robustness and interpretability of the regression results. The refined analysis confirmed that GM, MOQ, and stock levels have a positive and statistically significant effect on purchasing prices, while demand shows a negative effect—suggesting that increased demand may be associated with supplier discounts or economies of scale in procurement.

To capture more nuanced relationships, interaction terms (e.g., stockouts × MOQ, GM × demand) were introduced. These revealed that the effects of some variables are conditional on others, indicating that purchasing price is influenced by interdependent operational dynamics. However, the addition of interaction terms also increased multicollinearity, diminishing the individual significance of previously important predictors. Variance Inflation Factor (VIF) analysis is proposed as a next step to evaluate and address this issue.

Furthermore, the study explores potential endogeneity by regressing current purchasing prices on lagged values of the independent variables. The significance of these lagged variables suggests that past operational conditions have a persistent impact on present pricing decisions.

The findings hold practical implications for retail decision-makers. Understanding how GM targets, MOQ requirements, inventory levels, and demand trends influence purchasing prices enables retailers to develop more informed procurement strategies, negotiate better supplier terms, and optimize inventory management. These insights are especially critical for discount retailers where cost control and pricing efficiency directly impact profitability.

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CONTRIBUTION OF AUTHORS

The contributions of each author involved in this thesis are as follows:

Wintana Tadesse (Primary Author):

As the primary author of this thesis, I conducted the overall research, including data collection, analysis, and interpretation of results. I was responsible for developing the research questions, designing the methodology, and drafting the manuscript. I also managed the literature review, coordinated with external collaborators, and integrated machine learning techniques into the study. The conceptualization of the study, analysis of the results, and writing of the final draft were all led by me.

Associate Professor Salim Lahmiri (Thesis Advisor):

Associate Professor Salim Lahmiri provided invaluable guidance and mentorship throughout the research process. He helped refine the research questions and methodology, offering feedback and suggestions that shaped the direction of the study. His expertise in the field of machine learning and retail analytics was crucial in helping to fine-tune the analysis and enhance the overall quality of the work. He also contributed to the review and revision of the manuscript.

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CHAPTER 1
INTRODUCTION

1.0 INTRODUCTION

The retail industry operates within a complex and competitive environment where pricing strategies play a pivotal role in determining a retailer's success and profitability. Purchasing prices, the costs incurred by retailers to acquire goods from suppliers, are influenced by a multitude of factors that interact in dynamic ways. Understanding these factors is crucial for retailers aiming to optimize their procurement strategies, manage costs effectively, and enhance overall profitability.

This introduction sets the stage for exploring the various determinants of purchasing prices, including Minimum Order Quantity (MOQ), demand fluctuations, stock levels, and gross margin requirements. Each of these factors contributes to the pricing decisions retailers make, affecting their ability to negotiate favorable terms with suppliers and maintain competitive pricing in the marketplace. By examining these elements, the study aims to provide actionable insights that can guide retailers in refining their procurement practices and achieving better financial outcomes.

1.1 BACKGROUND OF THE STUDY

1.1.1 Overview of the retail industry

The retail industry is a crucial part of the global economy, encompassing diverse businesses from large chain stores and e-commerce platforms to local independent retailers. This sector is marked by its rapid evolution and complexity, driven by technological advancements, and changing consumer preferences (Grewal, Roggeveen, & Nordfält, 2017; Laudon & Traver, 2021). The rise of e-commerce has revolutionized retail, offering unprecedented convenience and access to global markets, while traditional formats continue to adapt by integrating new technologies to enhance the in-store experience.

Technological innovation plays a pivotal role in shaping retail operations, with advancements in artificial intelligence, big data analytics, and automation transforming inventory management and personalized marketing (Brynjolfsson & McElheran, 2016). Additionally, shifting consumer preferences for convenience, personalization, and sustainability necessitates that retailers innovate and adapt their offerings (Solomon, 2020). The globalized nature of industry has intensified competition, requiring retailers to navigate complex supply chains and regulatory environments while balancing operational efficiency with differentiation to maintain a competitive edge (Christopher, 2016; Dunning, 2015).

1.1.2 Importance of pricing in retail

Pricing is a critical aspect of the retail strategy, fundamentally influencing both competitive positioning and overall profitability. In the retail sector, where consumers have numerous choices and are highly price-sensitive, effective pricing strategies can significantly impact a retailer's success. Pricing decisions play a crucial role in attracting and retaining customers, optimizing revenue, and maximizing profit margins (Kotler & Keller, 2016).

Retailers employ a variety of pricing strategies to navigate the competitive landscape and respond to market conditions and consumer behavior. Dynamic pricing involves adjusting prices in real-time based on demand, competition, and other external factors. This approach allows retailers to capitalize on high-demand periods and optimize revenue (Elmaghraby & Keskinocak, 2003). Discounting and promotional offers are other common strategies used to stimulate sales, clear out inventory, or attract new customers. These tactics must be implemented with careful consideration to avoid eroding profit margins and to maintain the perceived value of the products (Nagle, Hogan, & Zale, 2016).

Effective pricing strategies must strike a balance between profitability and consumer appeal. Retailers must consider their cost structures, competitive positioning, and consumer expectations when setting prices. For instance, pricing too high may drive customers to competitors, while pricing too low may lead to reduced margins and perceptions of lower quality. Thus, pricing decisions are pivotal in shaping a retailer's financial performance, market position, and competitive advantage (Monroe, 2003). To succeed, retailers need to continuously evaluate and adjust their pricing strategies in response to changing market dynamics and consumer preferences.

1.1.3 Significance of understanding purchasing prices

Understanding the determinants of purchasing prices is crucial for retail enterprises as these costs directly affect profit margins and overall financial performance. Purchasing prices and costs are influenced by a range of factors that can impact a retailer's profitability and operational efficiency (Christopher, 2016).

Demand Fluctuations: The level of demand for products plays a significant role in determining purchasing prices. High demand can provide retailers with leverage to negotiate lower prices with suppliers, especially when suppliers are eager to secure large orders (Kox & van der Meer, 2015). Conversely, low demand might lead to higher purchasing prices or less favorable terms, as suppliers may increase prices to compensate for lower volumes (Wang, 2020). Retailers who can accurately forecast demand and adjust their purchasing strategies accordingly are better positioned to manage costs and enhance profitability.

Supply Chain Dynamics: The efficiency and stability of the supply chain significantly impact purchasing prices. Factors such as transportation costs, lead times, and inventory management practices can affect the cost of goods (Christopher, 2016). Disruptions in the supply chain, such as those caused by natural disasters, geopolitical issues, or logistical challenges, can lead to increased purchasing prices due to delays or shortages (Tang, 2006). Effective supply chain management and robust risk mitigation strategies are essential for maintaining stable purchasing prices and avoiding cost fluctuations.

Supplier Relationships: The nature of relationships between retailers and suppliers also influences purchasing prices. Strong, collaborative relationships with suppliers can lead to more favorable pricing terms, as suppliers may offer discounts or preferential pricing based on long-term partnerships and high-volume orders (Kraljic, 1983). Conversely, poor supplier relationships or a lack of negotiation leverage can result in higher prices and less favorable terms (Monczka et al., 2015). Retailers who invest in building and maintaining positive supplier relationships are better equipped to negotiate advantageous pricing and secure more stable supply terms.

Inventory Management: Effective inventory management is another critical factor influencing purchasing prices. Retailers who manage their inventory levels well can avoid stockouts and excess inventory, both of which can impact purchasing costs (Heizer & Render, 2017). For example, maintaining optimal inventory levels helps retailers negotiate better prices by demonstrating their ability to move products efficiently and reduce the risk of holding costs.

On the other hand, surplus inventory may provide leverage for negotiating lower prices or discounts, but it also requires careful management to avoid issues related to obsolescence and storage costs.

Therefore, understanding the various determinants of purchasing prices allows retailers to make informed strategic decisions regarding procurement and pricing. By navigating demand fluctuations, managing supply chain dynamics, fostering strong supplier relationships, and optimizing inventory management, retailers can enhance their financial performance and maintain a competitive edge in the market.

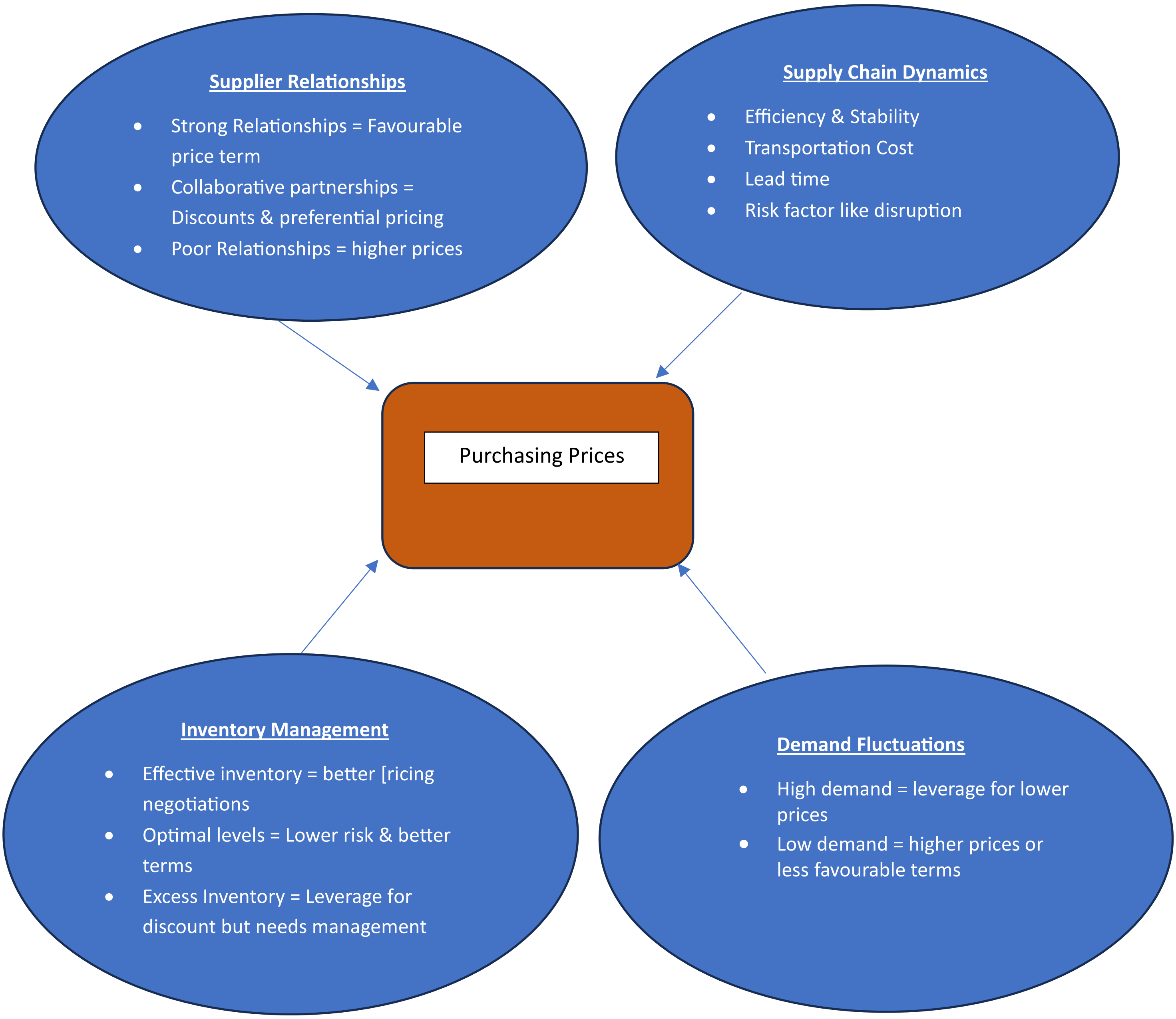


Figure I: Factors Influencing Purchasing Prices

1.2 RESEARCH PROBLEM AND OBJECTIVES

1.2.1 Identification of the research gap

Despite extensive theoretical and empirical research on purchasing prices in the retail sector, significant gaps remain that necessitate further investigation. Existing literature provides valuable insights into various factors influencing purchasing prices, such as Minimum Order Quantity (MOQ), demand fluctuations, stock levels, and gross margins. However, much of this research is either dated or lacks a comprehensive approach that integrates multiple factors simultaneously. For instance, while studies like those by Lal and Staelin (1984) and Chen (2003) address demand variability and inventory levels, they often do not account for the interplay between these factors or their combined effects on purchasing prices.

Furthermore, the rapidly evolving retail environment, characterized by the rise of e-commerce, global supply chain disruptions, and shifting consumer behaviors, presents new challenges that existing models may not fully address. Research by Grewal and Levy (2015) and Levy et al. (2004) touches upon competitive pricing and dynamic pricing strategies, yet there is a lack of empirical evidence on how these strategies interact with other determinants in contemporary retail settings. The complexity of modern supply chains and the integration of new technologies also necessitate updated models and methodologies that reflect current industry practices.

Addressing these gaps will require robust, empirical investigations that consider the multifaceted nature of purchasing price dynamics. By incorporating contemporary factors and employing advanced methodologies, future research can enhance our understanding of purchasing price determinants and inform more effective retail procurement strategies.

1.2.2 Research questions

To elucidate the relationship between key factors and purchasing prices in the retail sector, the following research questions are proposed:

1. How does Minimum Order Quantity (MOQ) influence purchasing prices in the retail sector?

This question aims to explore the extent to which MOQ affects the prices retailers pay for goods. It seeks to determine whether higher MOQs lead to lower per-unit prices and how this relationship varies across different retail segments and supplier relationships.

2. What is the impact of demand fluctuations on purchasing prices, and how do retailers adjust their procurement strategies in response to these fluctuations?

This question investigates how changes in consumer demand affect purchasing prices and how retailers modify their buying strategies to manage price volatility. It examines whether retailers can negotiate better terms during high demand periods or if they are forced to accept higher prices due to increased competition.

3. How do stock levels influence purchasing prices, and what role does inventory management play in negotiating favorable purchasing terms?

This question focuses on the relationship between inventory levels and purchasing prices. It seeks to understand how having either high or low stock levels impacts the prices retailers pay and how effective inventory management can aid in negotiating better deals with suppliers.

4. In what ways do gross margin requirements affect purchasing price decisions, and how do retailers balance margin goals with procurement costs?

This question aims to examine how the need to achieve specific gross margin targets influences purchasing prices. It explores how retailers reconcile the cost of goods with their margin objectives and the implications for pricing strategies and overall profitability.

By addressing these questions, the research aims to provide a comprehensive understanding of how various factors interact to influence purchasing prices in the retail industry.

1.2.3 Objectives of the study

Objective: Factors Influencing Purchasing Price Variability

The objective explores the critical factors contributing to retail purchasing price variability MOQ, consumer demand, stock levels, and gross margin within the framework of supply chain factors, economic conditions, and inventory decisions. These factors are key to understanding how pricing strategies are influenced and adjusted in response to market dynamics:

1. **Supply Chain Factors:**

MOQ: The minimum order quantity requirement is influenced by supply chain dynamics. Larger orders can lower per-unit costs, but the risks of holding large inventories or facing delays are also factors to consider. MOQ is a critical element in the supply chain, determining procurement strategies and influencing cost structures (Christopher, 2016).

Consumer Demand: Fluctuations in consumer demand, influenced by market conditions and broader economic trends, play a major role in setting prices. When demand spikes, prices may increase due to scarcity or production limitations, while low demand may lead to discounts or promotions. Forecasting demand accurately allows retailers to optimize their purchasing and pricing strategies (Chen et al., 2019).

2. **Economic Conditions:**

Gross Margin: Retailers set their price strategies with a focus on achieving a specific gross margin. This objective aligns with the retailer's economic conditions, such as market competition, cost structures, and inflation, all of which influence margin goals. A high margin might justify higher prices, while cost-cutting measures may lead to lower pricing strategies (Kotler & Keller, 2016).

3. **Inventory Decisions:**

Stock Levels: Inventory decisions, including whether to hold excess stock or maintain lean inventories, affect pricing strategies. High stock levels may lead to reduced urgency and greater pricing flexibility, while low stock levels can increase pricing power due to perceived scarcity (Simchi-Levi et al., 2017). Retailers must carefully balance stock levels to optimize pricing while avoiding excess holding costs or stockouts.

The interplay between these high-level categories like supply chain factors, economic conditions, and inventory decisions creates a dynamic environment in which retail purchase prices are constantly adjusting. Understanding how these elements interact provides a comprehensive framework for analyzing price variability in retail.

1.3 SIGNIFICANCE OF THE STUDY

Understanding and forecasting retail purchasing prices is essential for optimizing supply chain management and maintaining profitability. Retail purchasing prices directly impact inventory flow, demand generation, and supplier relationships. When retailers have a clear understanding of how prices fluctuate and what drives those changes, they are better equipped to make informed decisions about procurement and pricing strategies.

Several key factors influence retail purchasing prices, including minimum order quantities (MOQ), demand fluctuations, stock levels, and gross margin requirements. By carefully analyzing these elements, retailers can determine the optimal timing and quantity for purchases, negotiate more favorable terms with suppliers, and reduce the risk of overstocking or stockouts. Strategic procurement not only improves cost efficiency but also strengthens partnerships with suppliers by fostering transparency and long-term collaboration.

The practical implications of this approach are significant. Retailers gain greater control over their pricing and inventory strategies, allowing them to respond more quickly to market changes and consumer demand. Suppliers, in turn, benefit from a clearer understanding of retailer needs, enabling them to tailor their offerings and production schedules more effectively. Consumers also stand to gain, as improved pricing strategies can lead to better product availability and more competitive pricing in the market.

Ultimately, the ability to understand and manage retail purchasing prices empowers all players in the supply chain. It supports more agile and resilient operations, enhances profitability, and helps businesses maintain a competitive edge in an ever-evolving retail landscape.

1. Importance of Retail Price in Supply Chain Management

Retail prices play a central role in supply chain management by influencing both demand and cost control. It directly impacts consumer purchasing decisions, shaping inventory turnover, production schedules, and distribution logistics. A well-optimized retail price helps balance supply with demand, ensuring minimal stockouts and excess inventory, which in turn streamlines the supply chain. Moreover, effective pricing strategies foster better relationships with suppliers, facilitating advantageous terms and promoting flexibility in response to changing market conditions. As such, retail pricing is foundational to achieving a responsive, cost-effective supply chain (Christopher, 2016; Simchi-Levi et al., 2017).

2. Why It Is Important to Determine Factors That Impact Retail Price

Identifying the factors that influence retail prices—such as MOQ, consumer demand, gross margin, and stock levels—is critical to developing sound pricing strategies. These factors interact to shape retail pricing and can greatly affect profitability. For instance, a retailer's MOQ influences unit costs, while changes in consumer demand or stock levels may prompt price adjustments. Determining how these factors interact allows retailers to make informed decisions, ensuring they do not overcharge or undercharge for products, which could negatively affect sales or margins. Understanding these factors ensures that retailers can respond to market fluctuations proactively and remain competitive (Kotler & Keller, 2016; Bertsimas & Kallus, 2018).

3. Why It Is Important to Forecast Retail Purchasing Price

Forecasting retail purchase prices is essential for maintaining a competitive edge and improving profitability. Accurate price forecasting allows retailers to anticipate shifts in demand, economic conditions, and market trends, enabling timely adjustments to pricing strategies. Additionally, price forecasting supports better inventory management by ensuring that product prices are aligned with expected future market behavior. Ultimately, forecasting empowers retailers to make informed, strategic decisions that optimize profitability and market positioning (Chen et al., 2019; Simchi-Levi et al., 2017).

CHAPTER 2

LITERATURE REVIEW

2.0 OVERVIEW

The literature review in this chapter offers a thorough analysis of the extant scholarly works on pricing strategies in the retail sector, examining a variety of approaches, including competitive pricing, value-based pricing, and cost-based pricing. It explores the critical role that these factors play in defining retail pricing decisions, including Minimum Order Quantity (MOQ), Gross Margin (GM), Stock level, and market demand, in influencing purchasing prices. Furthermore, the chapter examines prior research on pricing models, providing a comprehensive understanding of both theoretical frameworks and empirical analyses that are instrumental in the development of effective pricing strategies. This summary establishes the groundwork for comprehending the intricate relationship between market dynamics, consumer behaviour, and pricing strategies, which is essential for retailers seeking to optimize their pricing practices and navigate the competitive landscape.

2.1 PRICING STRATEGIES IN RETAIL

2.1.1 Overview of Pricing Strategies

Pricing strategies in the retail industry are fundamental to determining a retailer's competitive positioning and overall profitability. Retailers employ various pricing strategies, including cost-based pricing, competition-based pricing, and value-based pricing, each tailored to specific market conditions, consumer behaviours, and business goals.

Cost-based pricing is a traditional approach where the retailer sets prices by adding a fixed markup to the cost of goods sold. This strategy ensures that all costs are covered, providing a straightforward method for achieving profitability (Nagle & Müller, 2018). However, while cost-based pricing offers simplicity, it may not fully account for external market factors such as consumer demand or competitor pricing, potentially limiting its effectiveness in highly competitive markets.

Competition-based pricing, or competitive pricing, is another prevalent strategy in the retail industry. In this approach, retailers set their prices based on the prices of their competitors, making it especially useful in markets with high transparency and intense competition (Grewal & Levy, 2015). By aligning their prices with or slightly undercutting those of competitors, retailers can maintain market share and appeal to price-sensitive consumers. However, this strategy can lead to price wars, where continuous undercutting may erode profit margins and detract from the unique value propositions that differentiate retailers from their competitors.

Value-based pricing focuses on the perceived value of a product to the customer, rather than the cost to produce it or the price set by competitors. This strategy is customer-centric, relying on a deep understanding of consumer needs, preferences, and their willingness to pay (Monroe, 2019). In the retail industry, value-based pricing can be particularly effective for premium products or brands with strong customer loyalty, allowing retailers to command higher prices. However, implementing this strategy requires sophisticated market research and a strong brand reputation, making it more complex and resource-intensive than other pricing strategies.

2.1.2 Pricing Dynamics in Low-Price Retail Chains

Low-price retail chains like Dollarama and Walmart operate within a highly competitive landscape, where pricing strategies are critical to maintaining their market position and profitability. These retailers rely on dynamic pricing models that allow them to adjust prices in response to market conditions, consumer demand, and competitive pressures.

Walmart, as a global retail giant, has implemented a "Everyday Low Price" (EDLP) strategy, which focuses on consistently offering low prices rather than relying on frequent promotions or discounts (Levy, Grewal, Kopalle, & Hess, 2004). This approach aims to build consumer trust and loyalty by providing predictable pricing, which is particularly appealing to price-sensitive customers. The EDLP strategy is underpinned by Walmart's extensive supply chain capabilities, enabling the retailer to reduce costs and pass on the savings to customers. However, this strategy also necessitates rigorous cost control and efficiency in operations to maintain profitability at lower price points.

Dollarama, on the other hand, operates a multi-price point strategy, where most items are priced below a certain threshold (typically $5), allowing for flexibility in product offerings while maintaining an overall perception of low prices (Pereira, 2019). This pricing model enables Dollarama to cater to a broad customer base by offering a variety of products at accessible price points. The challenge for Dollarama lies in balancing the need for low prices with the rising costs of goods, particularly in the face of inflation and currency fluctuations. The company's ability to source products at competitive prices and efficiently manage its supply chain is crucial to sustaining its pricing strategy.

The pricing dynamics in these low-price retail chains are further influenced by the competitive environment, where the presence of other discount retailers and the rise of e-commerce platforms exert additional pressure on pricing strategies (Chen, Marshall, & Nam, 2021). To remain competitive, these retailers must continuously assess and adjust their pricing models, considering factors such as consumer behavior, economic conditions, and technological advancements. The ongoing evolution of pricing strategies in low-price retail chains highlights the importance of agility and adaptability in responding to market demands while maintaining a focus on cost leadership and value delivery.

2.2 PREVIOUS STUDIES ON PRICING MODELS

Purchasing prices, which represent the cost at which retailers acquire goods from suppliers, are influenced by a complex interplay of factors that are crucial for optimizing procurement strategies, managing costs, and maintaining profitability. Key determinants include the Minimum Order Quantity (MOQ), demand fluctuations, stock levels, and gross margin requirements.

One significant factor is MOQ, the smallest quantity a supplier is willing to sell, which often leads to lower unit prices for larger orders due to reduced production and shipping costs (Christopher, 2016). However, higher MOQs can increase holding costs and risk overstocking, negatively impacting profitability if demand falls short of expectations. Demand fluctuations are another critical determinant; high demand can lead suppliers to raise prices due to increased competition, while low demand may prompt them to lower prices to clear inventory (Kembro, Näslund, & Olhager, 2017). Retailers must monitor demand trends to time their purchases effectively and avoid paying higher prices during peak periods. Additionally, stock levels influence purchasing prices: high inventory allows for negotiating better terms with suppliers, while low inventory may necessitate higher purchase prices to prevent stockouts (Mentzer, Stank, & Esper, 2008). Gross margin requirements further impact purchasing decisions, as retailers must balance purchasing prices with the need to maintain profitability, often necessitating price adjustments to stay competitive (Berman & Evans, 2013).

Several studies have examined these factors in depth. Lal and Staelin (1984) explored how demand variability influences purchasing prices, demonstrating that retailers facing high demand uncertainty negotiate lower prices to mitigate risk. Chen (2003) showed that higher inventory levels generally lead to lower purchasing prices due to economies of scale. Tang (2006) investigated MOQ's impact on pricing, finding that high MOQs often result in higher prices unless retailers can leverage strong supplier relationships. Smith and Achabal (1998) examined the link between gross margin targets and purchasing prices, revealing that retailers with aggressive margin goals negotiate lower prices. Finally, Simchi-Levi, Kaminsky, and Simchi-Levi (2008) analyzed how supply chain dynamics, including efficiency and lead times, influence purchasing prices, highlighting that efficient supply chains facilitate lower prices through reduced risks and costs. Other factors such as supplier relationships and broader market conditions, including economic trends and global disruptions, also play a role in determining purchasing prices, necessitating adaptability in procurement strategies (Chen, Paulraj, & Lado, 2004).

The methodology for investigating factors influencing purchasing prices in retail incorporates a range of approaches, blending quantitative, qualitative, and mixed-methods research. Quantitative methodologies are widely used, employing statistical models to analyze large datasets and uncover relationships between factors like Minimum Order Quantity (MOQ), demand, stock levels, and gross margin (Hair, Black, Babin, & Anderson, 2010). Techniques such as regression analysis quantify how variations in demand and inventory levels affect purchasing prices, providing insights into the direct impact of these variables on price negotiations. Econometric modeling, which includes macroeconomic variables like market trends and currency exchange rates, further enriches the analysis by contextualizing retail-specific factors within broader economic conditions (Greene, 2018). Additionally, surveys and structured questionnaires gather data from retailers and suppliers on purchasing practices, allowing statistical analysis to identify trends and influences (Creswell, 2014).

Qualitative methodologies complement quantitative approaches by offering in-depth insights into the contextual factors affecting purchasing prices. Case studies explore the purchasing strategies of specific retailers, shedding light on how they manage supplier relationships, negotiate MOQs, and address demand fluctuations (Yin, 2018). In-depth interviews with procurement managers and supply chain executives provide a deeper understanding of qualitative factors, such as supplier trust and long-term relationships, impact pricing decisions (Kvale, 2007). Mixed methods approach, combining both quantitative and qualitative techniques, provide a comprehensive view of the complexities involved. For instance, studies might use regression analysis to quantify the effects of stock levels on purchasing prices while employing case studies to examine these effects in various retail contexts (Tashakkori & Teddlie, 2010). Structural equation modeling (SEM) further enhances this understanding by assessing multiple relationships among variables, capturing both direct and indirect effects in the context of retail pricing dynamics (Hair et al., 2010).

Table 1: Summary of Literature review

Study/Reference	Main Purpose	Market/Data	Methods	Main Findings
Nagle & Müller (2018)	To examine cost-based pricing strategies in retail.	General retail market	Conceptual framework analysis of pricing strategies	Cost-based pricing ensures profitability but fails to account for external factors like competition and demand.
Grewal & Levy (2015)	To explore competitive pricing strategies and their impact on retail pricing.	Retail market with intense competition	Theoretical analysis, case studies	Competitive pricing helps retain market share but can lead to price wars and diminished margins.
Monroe (2019)	To analyze value-based pricing and its focus on customer-perceived value.	Premium and luxury goods retail	Case study analysis and conceptual approach	Value-based pricing allows for higher prices by targeting customer willingness to pay but demands strong market research.
Levy, Grewal, Kopalle, & Hess (2004)	To evaluate Walmart's "Everyday Low Price" (EDLP) strategy in a global context.	Walmart retail chain	Case study analysis of pricing model	EDLP builds customer trust but requires operational efficiency and cost control for profitability at lower prices.
Pereira (2019)	To investigate Dollarama's multi-price point strategy and its pricing challenges.	Dollarama discount chain	Case study of pricing strategy in low-cost retail	Multi-price point model enables flexible pricing but is challenged by rising product costs and inflation.
Chen, Marshall, & Nam (2021)	To assess the impact of e-commerce and competition on discount retail pricing strategies.	Discount retail chains and e-commerce	Literature review, market analysis	E-commerce competition requires continuous price adjustments to maintain competitiveness and market share.
Christopher (2016)	To explore how Minimum Order Quantity (MOQ) impacts pricing in retail.	Retail supply chain data	Empirical and conceptual analysis of MOQ	Higher MOQs reduce unit prices but increase holding costs, potentially affecting profitability if demand is volatile.
Kembro, Näslund, & Olhager (2017)	To examine how demand fluctuations influence retail	Retail supply chains	Regression modeling and data analysis	Demand variability causes suppliers to raise prices during high demand and

	pricing and procurement.			lower them in low demand periods.
Mentzer, Stank, & Esper (2008)	To investigate the effect of inventory levels on purchasing prices in retail.	Retail supply chain data	Statistical analysis, econometric modeling	Higher stock levels enable better price negotiations, leading to lower procurement costs.
Berman & Evans (2013)	To study the influence of gross margin requirements on retail pricing decisions.	Retail procurement strategies	Case study and conceptual analysis	Gross margin goals directly influence pricing decisions, requiring balance between cost and profitability.
Lal & Staelin (1984)	To explore how demand uncertainty affects pricing decisions in retail.	Retail sector with demand uncertainty	Empirical analysis with regression modeling	Demand uncertainty drives retailers to negotiate lower prices to minimize risk, especially in volatile markets.
Chen (2003)	To assess the impact of inventory levels on retail purchasing prices.	Retail supply chains	Empirical study, regression models	Higher inventory levels result in lower purchasing prices due to economies of scale and bulk buying.
Tang (2006)	To analyze the impact of MOQ on pricing in retail procurement.	Retail supply chains	Regression analysis and empirical testing	Large MOQs often lead to lower unit prices but can increase holding costs, especially when demand is uncertain.
Simchi-Levi, Kaminsky, & Simchi-Levi (2008)	To assess how supply chain efficiency affects retail pricing.	Retail supply chains	Supply chain modeling, conceptual analysis	Efficient supply chains lead to lower procurement costs, facilitating competitive retail pricing.
Chen, Paulraj, & Lado (2004)	To evaluate how supplier relationships influence retail pricing strategies.	Retail supply chain and supplier relationships	Case studies, empirical analysis	Strong supplier relationships help secure better pricing terms and reduce procurement costs.
Hair, Black, Babin, & Anderson (2010)	To explore the role of quantitative methods in pricing decisions.	Retail data on MOQ, demand, and stock levels	Regression modeling and statistical analysis	Quantitative models reveal how factors like MOQ and stock levels affect pricing and purchasing decisions.

Greene (2018)	To study the impact of macroeconomic conditions on retail pricing strategies.	Macro and retail economic data	Econometric modeling and macroeconomic analysis	Macroeconomic factors (e.g., inflation) influence retail pricing alongside supply and demand-specific factors.
Yin (2018)	To investigate the role of case studies in understanding pricing strategies in retail procurement.	Retail pricing and procurement case studies	Case study methodology and qualitative analysis	Case studies highlight the importance of supplier relationships and negotiations in retail pricing decisions.
Tashakkori & Teddlie (2010)	To explore the benefits of mixed-methods research in retail pricing analysis.	Retail pricing and procurement data	Mixed-methods approach combining quantitative and qualitative data	Mixed methods provide a holistic view, capturing complex relationships between factors like MOQ, stock levels, and pricing.

2.3 LIMITATIONS OF THE LITERATURE AND CONTRIBUTIONS TO THE FIELD

2.3.1. Limitations of Literature:

Despite the comprehensive body of literature on pricing strategies in the retail sector, several gaps remain that limit the depth of understanding regarding the intricate relationships between various factors influencing purchasing prices. One key limitation is the lack of focus on the dynamic, real-time factors that shape retail pricing decisions in today's fast-paced, technology-driven environment. While traditional pricing models like cost-based, competition-based, and value-based pricing are well-documented, these models do not fully account for the rapid changes in consumer behavior, demand fluctuations, and the impact of e-commerce platforms on retail pricing (Grewal & Levy, 2015; Monroe, 2019). Furthermore, these traditional models are often static and do not adapt to the continuous shifts in market conditions and consumer expectations (Nagle & Müller, 2018).

Additionally, much of the existing research tends to examine individual factors in isolation, such as the influence of Minimum Order Quantity (MOQ) or gross margin targets on purchasing prices. However, there is limited exploration of how these factors interact in complex, multi-dimensional retail environments. For instance, while MOQ requirements are linked to lower unit costs, they can also increase holding costs and risks (Christopher, 2016). The combined effect of MOQ, demand fluctuations, and inventory management on overall pricing strategies remains underexplored (Simchi-Levi et al., 2008). Moreover, much of the research tends to oversimplify pricing dynamics by treating each factor as an independent variable, rather than exploring the interdependencies between them in the context of real-world retail operations (Tang, 2006).

Another significant gap in the literature is the lack of empirical research specifically focusing on low-price retail chains like Dollarama and Walmart. While broader studies have examined pricing strategies in retail, the unique challenges faced by discount retailers such as price elasticity, competitive pressures, and operational cost constraints have not been adequately addressed (Pereira, 2019; Levy et al., 2004). Discount retailers face unique pricing constraints that require continuous adaptation to low-cost, high-volume models, which significantly differ from traditional pricing strategies employed by premium brands (Monroe, 2019).

2.3.2. Contributions to the Field of Retail Pricing:

Incorporating Dynamic, Real-Time Factors in Pricing Models: This study directly addresses the gap in existing research where traditional pricing models (cost-based, competition-based, and value-based pricing) fail to account for the rapidly changing and dynamic nature of consumer behavior, demand fluctuations, and the influence of e-commerce on retail pricing. By incorporating real-time data into machine learning (ML) models, this study enables retailers to develop more adaptive pricing strategies that can effectively respond to these fast-paced, technology-driven market conditions, providing a much-needed shift towards dynamic and real-time pricing.

Exploring the Interactions Between Key Pricing Factors: One of the major limitations of prior work is the isolated treatment of key factors such as Minimum Order Quantity (MOQ), gross margin targets, and demand fluctuations. This study fills this gap by exploring the complex interrelationships between these variables and how they collectively impact retail pricing strategies. Through comprehensive analysis, this study emphasizes the interconnectedness of these factors and provides a more robust framework for understanding how their combined effect can be leveraged for more effective pricing decisions.

Empirical Research on Low-Price Retail Chains: The unique challenges faced by low-price retail chains such as Walmart and Dollarama have often been overlooked in previous studies. This study focuses specifically on these discount retailers, investigating how factors like price elasticity, operational cost constraints, and competitive pressures shape their pricing strategies. By providing empirical insights into the pricing dynamics of low-price retail chains, this study offers valuable knowledge that can guide these retailers in navigating their unique challenges while maintaining profitability and competitiveness in the marketplace.

Providing a Holistic Understanding of Pricing Dynamics: A significant contribution of this study is its ability to integrate a wide range of factors (MOQ, demand, stock levels, supplier relationships, etc.) into a cohesive pricing model. Unlike previous studies that have tended to focus on single variables in isolation, this study offers a more comprehensive, multi-faceted approach to understanding the complex dynamics of retail pricing. It provides retailers with a more nuanced framework for making data-driven decisions that consider the full spectrum of factors that influence pricing in today's competitive retail environment.

Actionable Insights for Retailers: Beyond theoretical contributions, this study provides actionable insights that directly benefit retail managers, particularly those in low-price retail chains. By leveraging the findings of this research, retailers can make more informed decisions about procurement, adjust their pricing strategies to respond to demand shifts, and strengthen supplier relationships. These practical insights will help retailers optimize their inventory management, reduce costs, and improve profitability, ultimately allowing them to maintain a competitive edge in the retail market.

In summary, this study addresses significant gaps in the existing literature by combining real-time market data with regression Model, exploring the interplay between multiple pricing factors, and focusing on the specific challenges of low-price retail chains. The insights provided will not only advance academic understanding but also offer practical, strategic recommendations for retailers looking to optimize their pricing and procurement processes in an increasingly complex and competitive retail landscape.

CHAPTER 3

METHODOLOGY

3.0 GENERAL

The methodology of this research is designed to thoroughly investigate the factors influencing purchasing prices in the retail sector, ensuring robust and nuanced findings (Lee et al., 2013). Data collection is carried out using secondary sources, primarily Enterprise Resource Planning (ERP) databases. The selection of variables, including cost of goods sold, market demand, and competition intensity, is based on an extensive literature review and expert consultations, ensuring both relevance and depth. To analyze the data, we employ analytical techniques, such as regression analysis. Performance metrics, including mean squared error and p-values, are used to evaluate model accuracy. This comprehensive approach ensures transparency and reproducibility, providing a solid foundation for understanding the complex dynamics of retail purchasing prices.

The methodology employs statistical techniques to examine the impact of key factors—such as Minimum Order Quantity (MOQ), demand fluctuations, stock levels, and gross margin requirements—on retail purchasing prices. By analyzing these variables, the study aims to understand the individual and combined contributions of each factor to pricing decisions. This approach provides a data-driven foundation for identifying the most influential elements affecting procurement costs. Ultimately, the study offers a comprehensive analysis of the underlying drivers of retail pricing decisions, supporting more strategic and informed decision-making across the supply chain.

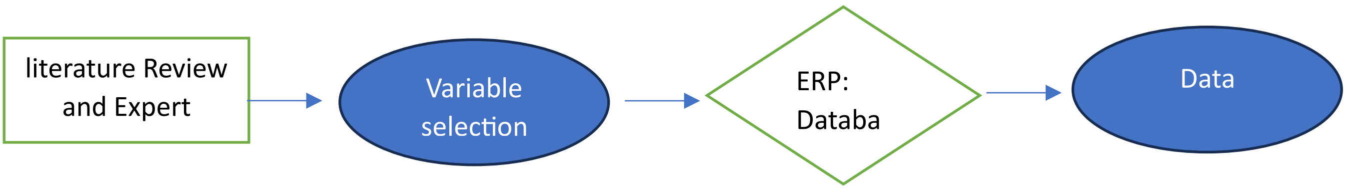


Figure II: Data collection

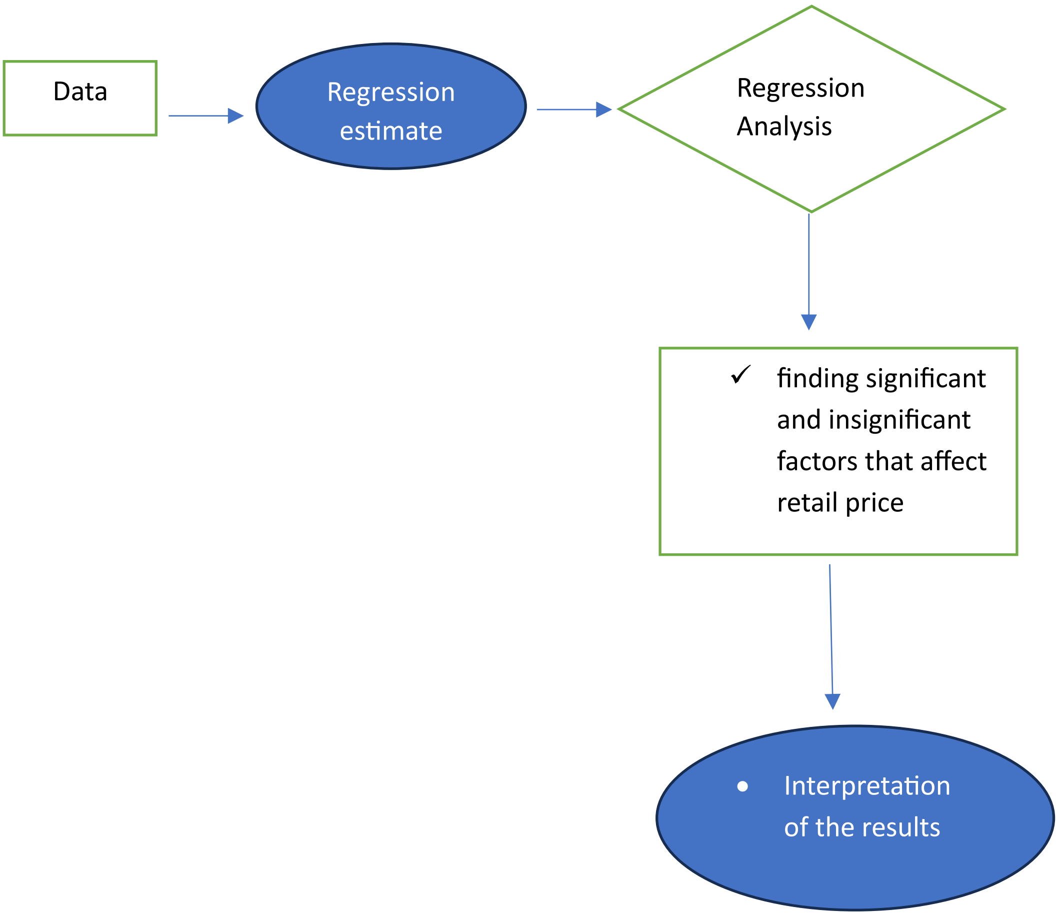


Figure III: Data Analysis - OLS – Regression Analysis

3.1 DATA COLLECTION AND DESCRIPTION

3.1.1 Description of the Dollarama Dataset

The dataset utilized in this study is sourced from Dollarama, a leading retail chain known for offering a wide range of products at competitive prices. It includes various key metrics related to products and financial performance, crucial for analyzing the factors influencing purchasing prices. One of the primary components is the number of Stock Keeping Units (SKUs), representing the total number of unique products available. The dataset includes information on 2,791 SKUs. This metric provides insight into the diversity of Dollarama's inventory (refer to Data_Collection). Additionally, the dataset includes detailed information on the vendors, which encompasses the number of suppliers, the specific products they supply, and other relevant details. This data is essential for understanding the supply chain dynamics and sourcing strategies employed by Dollarama (Oldfield, 2019).

The purchasing prices in the dataset represent the costs at which Dollarama procures goods from its vendors. These prices are a critical aspect of the analysis, as they directly affect the retail prices and profit margins. The dataset also contains information on the Minimum Order Quantity (MOQ), which is the least number of units that must be purchased from a vendor in a single order. This metric is important for analyzing the impact of bulk purchasing on cost efficiency and inventory management.

Another crucial component of the dataset is the Gross Margin (GM), which represents the profitability of each product by calculating the gross profit margin. GM is determined by subtracting the purchasing price from the selling price and expressing the result as a percentage of the selling price. This metric is vital for evaluating the financial performance of individual products and entire categories, allowing businesses to identify their most profitable offerings.

In addition to GM, the dataset includes historical sales data, which provides valuable insights into demand patterns across different products. These demand metrics encompass both the volume and frequency of purchases, offering a detailed view of consumer behavior. By analyzing this data, businesses can more accurately predict future sales trends, enabling more effective demand forecasting and inventory planning. The final component is Stock levels, refers to the quantity of a product that a retailer has available for sale at any given time. The current stock level for each SKU as recorded in the company database system. The average stock level for each SKU was calculated to provide a consistent and reliable measure of inventory availability.

The dataset covers a twelve-month period, offering a longitudinal view of Dollarama's product and financial metrics. It spans a wide range of products across various categories, providing a robust and comprehensive basis for analysis. This detailed data set enables an in-depth exploration of the factors influencing purchasing prices in the retail sector, facilitating the development of predictive models and strategic insights.

3.1.2 Data Sources and Acquisition

The data for this study was sourced from Dollarama's internal database (SAP), with permissions granted explicitly for research purposes. The acquisition process strictly adhered to data privacy regulations and ethical standards, ensuring that sensitive information, such as vendor identities and exact pricing details, was anonymized to protect confidentiality. The data was collected through secure channels and stored in a protected environment to maintain data integrity and security.

Data preprocessing was a crucial step to ensure the quality and consistency of the dataset. The process began with data cleaning, which involved identifying and addressing missing or inconsistent data entries. Depending on the extent and significance of the missing data, techniques such as imputation or exclusion were used to handle these issues. Following data cleaning, data transformation was performed to normalize and standardize variables, ensuring comparability across different data points. For instance, purchasing prices were adjusted for inflation, and all monetary values were standardized to a common currency to account for temporal and currency variations.

3.2 VARIABLE SELECTION AND JUSTIFICATION

3.2.1 Identification of Key Variables

The identification of key variables for this study was based on a thorough review of both theoretical and empirical literature concerning pricing strategies and procurement in the retail sector. The selection process focused on variables that are crucial for understanding the factors influencing purchasing prices. One of the primary independent variables chosen is the Minimum Order Quantity (MOQ), which represents the minimum number of units a vendor requires a retailer to purchase in a single order (Chow, 2011). MOQ is significant as it can influence purchasing prices through economies of scale, with vendors often offering discounts for larger orders. Another critical variable is the Gross Margin (GM), which indicates the profitability of each product by calculating the difference between the selling price and the purchasing price as a percentage of the selling price. This metric is essential for understanding how profit potential affects pricing strategies and product prioritization (Kolias & Arnis, 2019).

Additionally, the dataset also includes Demand Metrics, such as historical sales volume and frequency, providing insights into consumer demand patterns. These metrics are crucial for forecasting future demand, optimizing inventory levels, and negotiating prices with vendors based on anticipated consumer demand. By focusing on these variables, the study aims to uncover the dynamics that drive pricing strategies and procurement decisions in the retail sector, providing valuable insights into how retailers can optimize their purchasing processes.

Stock level refers to the quantity of a product that a retailer has available for sale at any given time. It is a key variable in managing purchasing prices due to its impact on supply chain efficiency and customer satisfaction. Maintaining optimal stock levels helps retailers avoid stockouts, which can result in lost sales and customer dissatisfaction. Efficient stock management can lead to better purchasing decisions and lower prices.

3.2.2 Operationalization of Variables

To ensure precise measurement and analysis, the key variables in this study were carefully operationalized using specific metrics. The Minimum Order Quantity (MOQ) was measured in units, representing the minimum number of items a retailer is obligated to purchase from a vendor in a single transaction. This metric is crucial for understanding the purchasing constraints faced by retailers and the opportunities for leveraging bulk buying to achieve economies of scale. A higher MOQ typically means better price negotiations due to larger volume purchases, but it also implies greater financial commitment from the retailer, which can impact cash flow and inventory management.

The Gross Margin (GM) was calculated to gauge the profitability of each product. This was done using the formula:

$$GM = MU\% \times Purchasing\ price \times unit\ sold$$

This expresses GM as a Canadian Dollar amount, providing a straightforward indicator of the amount of dollar of revenue that is gross profit. A higher GM indicates more significant profit potential, which can influence a retailer's decision to stock certain products or negotiate better terms with vendors. This metric is vital for assessing the financial health of different product lines and understanding how pricing strategies impact overall profitability.

Demand was operationalized as the average monthly sales volume over the past 12 months. This approach allowed for a stable and representative measure of product popularity and consumer demand, smoothing out temporary fluctuations. To further ensure comparability across time periods, the sales data was normalized to account for seasonal effects, promotional events, and other temporary anomalies (Hançerlioğulları et al., 2016). This normalization process adjusted the raw data to a common scale, enabling consistent interpretation of demand patterns throughout the year. By focusing on long-term trends rather than short-term spikes, the measure of demand provided a reliable basis for forecasting future sales and guiding purchasing decisions.

Stock Out was defined as the proportion of expected sales lost due to product unavailability. Specifically, it was measured as a percentage: the value of stockouts relative to expected sales, based on the same 12-month average demand used in the demand calculation. This provided a consistent reference point for identifying whether supply consistently failed to meet consumer demand over time.

By operationalizing the variables out in this way, the study was able to rigorously assess their impact on purchasing price, defined here as the landed cost of a product excluding any applicable duty rates. This structured and data-driven approach ensured that the variables were both accurate and relevant for drawing actionable insights in the context of retail supply chain and pricing strategy.

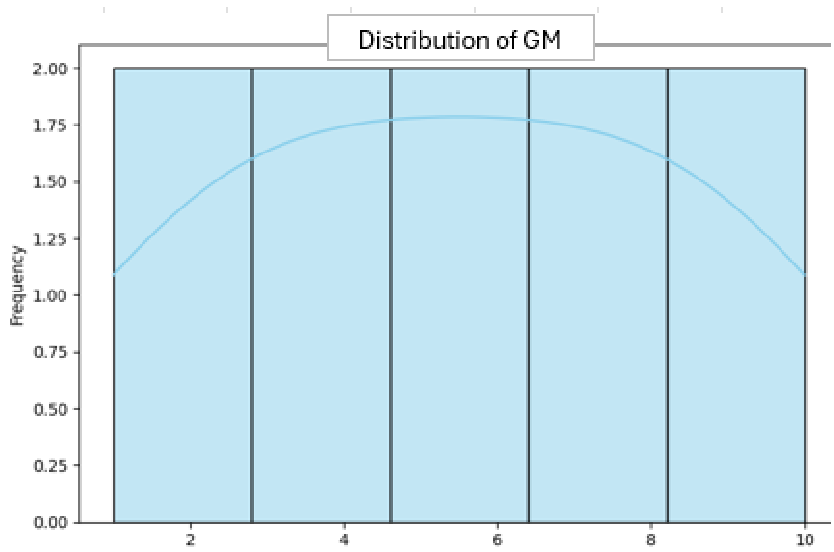


Figure 1: Distribution of Gross Margin (GM)

Figure 1 illustrates the distribution of gross margin across the dataset. The GM histogram shows that most products have a gross margin clustered around the mid-range percentages. Which coincides with the Figure 2 distribution of Demand. This distribution suggests that while some products have high profitability, the majority have modest gross margins.

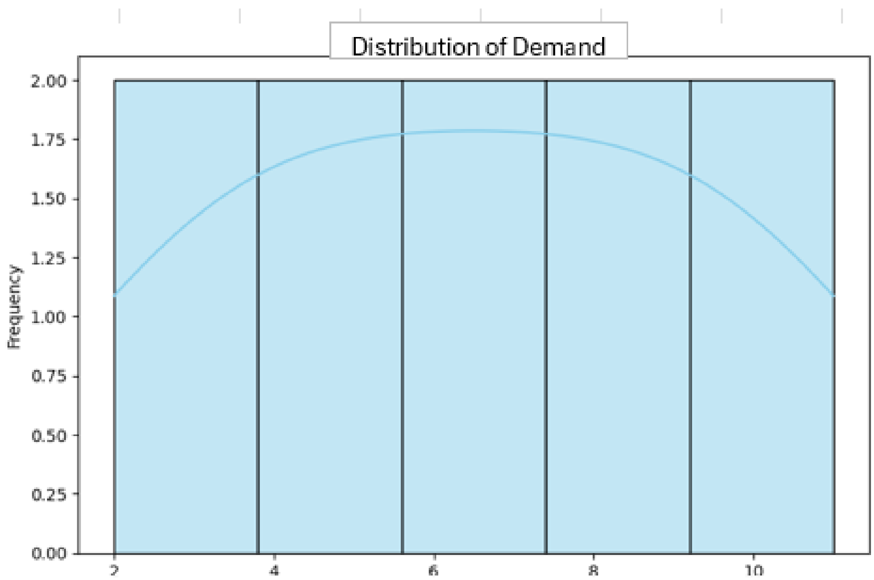


Figure 2: Distribution of Demand

The demand metrics histogram shows a broad distribution, with many products experiencing moderate demand. This insight into consumer behavior can guide inventory and pricing strategies. Additionally, this distribution aligns with the gross margin data, indicating that higher demand generally leads to greater profitability.

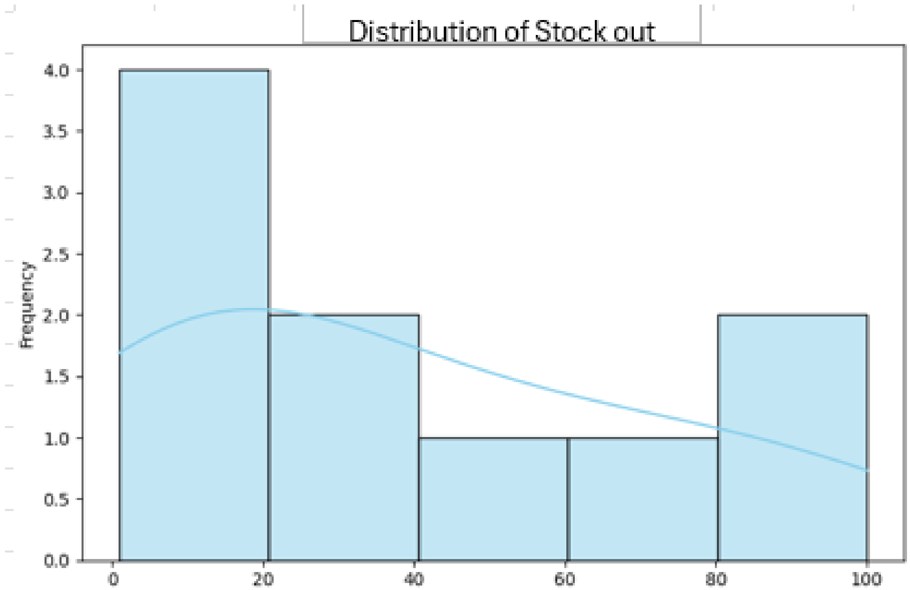


Figure 3: Distribution of Stock out (Stock level)

The histogram of stock-out metrics provides valuable insights into our inventory levels. Specifically, it shows a lower frequency of stock-outs in the midsection of the distribution. This observation supports the notion that maintaining higher stock levels enables us to meet greater demand. As a result, we can sell more products, which is reflected in increased demand and ultimately leads to higher profitability, as indicated by improved gross margins (GM). This reinforces the relationship between adequate stock levels and enhanced sales performance.

3.2.3 Justification for Variable Inclusion

The inclusion of these variables in the study is carefully justified based on their critical relevance to understanding the dynamics of purchasing prices in the retail sector. Each variable was selected to provide comprehensive insights into different aspects of the pricing and procurement process, offering a holistic view of the factors influencing purchasing decisions.

The Minimum Order Quantity (MOQ) and Gross Margin (GM) are particularly important for understanding vendor pricing strategies and cost structures. MOQ directly affects the purchasing cost, as vendors often offer lower prices per unit when larger quantities are ordered, reflecting economies of scale. This variable helps to analyze how purchasing volume can influence cost savings and pricing negotiations. On the other hand, GM provides a measure of profitability for each product, indicating the portion of sales revenue that exceeds the cost of goods sold. By analyzing GM, the study can assess the effectiveness of pricing strategies and how they align with overall financial goals, such as maximizing profit margins.

Including stock level as a variable is also essential because stock levels directly influence purchasing decisions and pricing strategies. Low stock levels may indicate increased demand or potential scarcity, prompting retailers to secure additional inventory at higher prices to avoid stockouts. Conversely, high stock levels may suggest overstocking or slow-moving items, leading to lower purchasing prices as retailers negotiate discounts to clear excess inventory. Additionally, high stock levels can increase inventory holding costs, which retailers may offset by negotiating lower purchase prices, making stock levels a critical factor in price negotiations with suppliers.

Demand Metrics, which encompass historical sales volume and frequency, are crucial for understanding how market demand influences purchasing decisions and pricing. By analyzing these metrics, the study can identify trends in consumer behavior and demand patterns, which are essential for making informed purchasing decisions. High demand for certain products can lead to increased purchasing prices due to higher competition for stock, while lower demand may result in discounted prices. Additionally, demand metrics help retailers forecast future sales and adjust their pricing strategies, accordingly, ensuring they meet market needs while maintaining profitability.

3.3 ORDINARY LEAST SQUARES (OLS) REGRESSION ANALYSIS

3.3.1 Overview of OLS Regression

Ordinary Least Squares (OLS) regression is a statistical technique used to estimate the relationships between one dependent variable and one or more independent variables. In this study, OLS regression is utilized to analyze the influence of selected independent variables—such as Minimum Order Quantity (MOQ), Gross Margin (GM), Stock level, and Demand Metrics on the dependent variable, purchasing prices. The primary goal of using OLS regression is to determine how changes in the independent variables are associated with changes in purchasing prices (Mura et al., 2018).

One key merit of using regression models in determining the statistical significance of each key factor on retail price is their ability to quantify the relationship between multiple independent variables (such as MOQ, demand fluctuations, stock levels, and gross margin) and the dependent variable (retail price). Regression models provide clear, interpretable coefficients that indicate the strength and direction of these relationships, allowing for a detailed understanding of how each factor impacts pricing decisions. Moreover, regression models can assess the statistical significance of these factors by providing p-values, helping to identify which factors have a meaningful influence on retail prices and which do not. This makes regression models a powerful tool for isolating key drivers of price changes and guiding data-driven pricing strategies.

In addition, using a regression model before deploying more complex machine learning models can be highly beneficial for multiple reasons. First, a regression model serves as a useful baseline to compare against more sophisticated algorithms, helping to determine if the added complexity yields real improvements in predictive performance (James et al., 2013). Regression models are also simpler and more interpretable, allowing for better understanding of variable relationships and insights into the data, which can be essential when explaining results to non-technical stakeholders (Hastie, Tibshirani, & Friedman, 2009). Additionally, regression analysis can help identify important features, guiding feature selection for more complex models and improving their efficiency (James et al., 2013). The simplicity of regression models also makes them ideal for spotting data issues such as multicollinearity, outliers, or non-linearity, which can then be addressed before applying more advanced techniques (Hastie et al., 2009). Regression models are less computationally intensive, enabling quicker iteration and preliminary analysis, which saves both time and resources. Lastly, in cases where the problem's data structure is straightforward and linear, regression models may achieve comparable predictive power to more complex algorithms (James et al., 2013). Thus, starting with a regression model provides a solid foundation for deeper exploration and ensures that the transition to more complex machine learning models is well-justified

3.3.2 Model Specification

The regression model employed in this study is specified to understand the relationship between purchasing prices and various independent variables. The model is formulated as follows:

$$Landed\ Cost_{\ i} = \beta_0 + \beta_1 Gross\ margin_i + \beta_2 Demand_i + \beta_3 MOQ_i + \beta_4 Stock\ level_i + \epsilon_i$$

Where:

- $Landed\ Cost_{\ i}$ is the landed cost for SKU i
- β_0 is the intercept term.
- $\beta_1, \beta_2, \beta_3, \beta_4$ are the coefficients for the explanatory variables.
- ϵ_i is the error term.

These coefficients measure the change in purchasing price associated with a one-unit change in each independent variable, holding all other variables constant. ϵ is the error term, representing the variation in purchasing prices that cannot be explained by the independent variables included in the model (Chaudhari, 2014).

The inclusion of these variables allows the model to capture the core determinants of purchasing prices, providing a comprehensive analysis of how each factor contributes to the overall pricing dynamics. Additionally, control variables such as product category and seasonal factors are included in the model to account for external influences that may affect purchasing prices. Product category control variables help differentiate the effects of pricing strategies across different types of products, while seasonal factors control fluctuations in purchasing prices due to seasonal variations, such as holiday demand or off-season discounts. These controls are crucial for isolating the specific impact of the main independent variables on purchasing prices, ensuring that the results are not confounded by extraneous factors. This regression model, through its specification and inclusion of relevant controls, aims to provide a detailed and accurate understanding of the factors influencing purchasing prices in the retail sector, facilitating more informed decision-making and strategic planning.

3.3.3 Estimation Procedure

The estimation procedure for the regression model involves using statistical software, such as SAS and Python, to fit the model to the data (Makkar et al., 2021). In this study, SAS software was used for regression estimation. This process begins with the input of the dataset, followed by the specification of the model, which includes the dependent variable (purchasing prices) and the independent variables (MOQ, GM, Stock level, Demand Metrics). The software uses these inputs to estimate the coefficients for each variable, representing their respective contributions to the dependent variable. To evaluate the fit of the model, several statistical metrics are employed. The R-squared (R^2) value is a key indicator, measuring the proportion of the variance in the dependent variable that is predictable from the independent variables. A higher R^2 value indicates a better fit, as it signifies that a greater portion of the variability in purchasing prices is explained by the model. Alongside R^2, the adjusted R-squared value is also considered, which adjusts the R^2 value based on the number of predictors in the model, providing a more accurate measure of model fit when multiple independent variables are included.

The F-test is conducted to assess the overall significance of the model. This test evaluates whether the model provides a better fit to the data than a model with no independent variables. A significant F-test result suggests that the independent variables, collectively, have a meaningful relationship with the dependent variable and that the model is statistically significant (Satria & Komara, 2020). To determine the significance of individual coefficients, t-tests are used. These tests evaluate whether each independent variable significantly contributes to the model by testing the null hypothesis that the coefficient is equal to zero (no effect). A low p-value (typically less than 0.05) indicates that the corresponding coefficient is significantly different from zero, suggesting that the variable has a meaningful impact on purchasing prices. This estimation procedure, using statistical software and comprehensive testing, ensures the robustness and reliability of the regression model. By assessing both the overall fit and the significance of individual variables, the study can provide detailed insights into the factors that influence purchasing prices in the retail sector.

3.4 MODEL DEVELOPMENT AND EVALUATION

The selection of appropriate models in this study is guided by the specific characteristics of the data and the research objectives, with a focus on complexity, interpretability, and computational efficiency. These criteria ensure that the models provide actionable insights without overcomplicating the analysis or introducing unnecessary complexities that might lead to overfitting. A key consideration in this process is the ability of the model to capture the relationships between important variables such as Minimum Order Quantity (MOQ), demand fluctuations, stock levels, and gross margin requirements. It is essential that the model balances the need to capture these relationships while remaining understandable and efficient.

Interpretability is particularly critical in the business context of this study, where decision-makers need clear, understandable results to inform retail pricing strategies. Ordinary Least Squares (OLS) regression is well-suited for this purpose, as it is a linear model that produces straightforward coefficients, quantifying the influence of each independent variable. This makes OLS regression not only a transparent tool but also one that is practical for making strategic procurement decisions. By offering clear and interpretable results, OLS allows stakeholders to confidently communicate and justify pricing strategies, facilitating informed decision-making.

Computational efficiency further strengthens the case for OLS regression. It is relatively simple to implement, requires minimal computational resources, and delivers results quickly, even when analyzing large datasets. These characteristics make OLS regression an ideal tool for iterative analyses and real-time applications, where the ability to process data efficiently and provide timely results is crucial.

Given these advantages, OLS regression was selected as the primary modeling technique in this study. It effectively balances the need for interpretability and efficiency while providing robust insights into the factors influencing retail purchasing prices. OLS regression's clarity, simplicity, and practical relevance make it a valuable tool in guiding procurement strategies and enhancing pricing decision-making (Friedman, 2001).

The methodology employed in this study provides a comprehensive and systematic framework for analyzing the factors influencing purchasing prices in the retail sector. Centered on traditional statistical techniques, specifically OLS regression, this approach offers a structured way to explore and quantify the relationships between key variables that drive procurement costs. The transparency and ease of interpretation that OLS regression offers make it particularly suitable for this type of analysis, allowing the identification of statistically significant predictors and providing clarity about how each factor contributes to price variations.

Through the use of OLS regression, the study evaluates the individual and combined effects of factors such as MOQ, Gross Margin (GM) requirements, stock levels, and demand fluctuations. This method enables a clear understanding of which variables have the most impact on purchasing prices and helps pinpoint the drivers of cost fluctuations. Moreover, OLS regression facilitates effective variable selection, identifying the most important factors for inclusion in future pricing models.

To ensure the robustness and reliability of the findings, the methodology includes rigorous evaluation metrics and validation techniques. These encompass tests for multicollinearity, residual analysis, and goodness-of-fit measures, which help confirm the validity of the regression model and its applicability to the broader retail context.

Ultimately, the analytical approach outlined in this study offers valuable, data-driven insights that can guide pricing strategies and procurement decisions in the retail industry. By leveraging OLS regression, a well-established and efficient statistical tool, the study provides retailers with a clearer understanding of market dynamics, improves supplier negotiations, and optimizes financial performance in a competitive retail environment.

CHAPTER 4

DATA DEVELOPMENT AND EVALUATION

4.0 OVERVIEW

This chapter aims to provide a comprehensive analysis of the Dollarama dataset to understand the underlying factors influencing purchasing prices in the retail sector. By examining key variables such as Minimum Order Quantity (MOQ), demand fluctuations, stock levels, and gross margin requirements, the statistical model developed here offers valuable insights into how these factors interact and contribute to price determination. The model provides actionable guidance for retail businesses to optimize their pricing strategies by identifying the most impactful drivers of price changes. It also helps refine procurement processes by clarifying how factors like MOQ and stock levels influence purchasing costs, enabling more efficient inventory management. Furthermore, the model supports improved supplier negotiations by equipping retailers with data-driven insights to secure better terms. Ultimately, the analysis helps businesses make informed decisions that enhance profitability, optimize operational efficiency, and strengthen supplier relationships in an increasingly competitive market.

4.1 DOLLARAMA DATASET: OVERVIEW AND DESCRIPTIVE ANALYSIS

4.1.1 Characteristics of the Dataset

The Dollarama Dataset is an extensive collection encompassing over 2,000 Stock Keeping Units (SKUs) sourced from more than 200 different vendors. This dataset serves as a comprehensive resource for analyzing the factors that influence purchasing prices in the retail sector. It includes a variety of key variables, such as purchasing prices, Minimum Order Quantity (MOQ), Gross Margin (GM), stock level, and metrics related to demand. The inclusion of these variables allows for a nuanced analysis of the factors that can impact pricing strategies and decision-making in a retail context. The diversity of products and vendors within the dataset provides a rich and varied dataset that is well-suited for understanding the complexities of retail pricing. The SKUs cover a wide range of product categories, reflecting the broad assortment typically found in a retail environment like Dollarama. This diversity is crucial for capturing the full spectrum of factors that can influence purchasing prices, including differences in product types, vendor negotiations, and market demand conditions (Rooderkerk et al., 2013).

The dataset was sourced directly from Dollarama's internal records, ensuring a high level of accuracy and reliability. This internal data collection process is advantageous because it minimizes the risk of errors or inconsistencies that can occur when data is aggregated from multiple external sources. Moreover, using internal records allows for a more detailed and granular view of the data, capturing nuances that might be lost in more generalized datasets.

Adhering to ethical standards and data privacy regulations was a priority in the data acquisition process. This involved anonymizing sensitive information to protect the privacy of vendors and customers involved in the transactions. The dataset includes de-identified vendor IDs and SKU numbers, ensuring that while the data remains highly useful for analysis, it does not compromise the confidentiality of any parties. This careful handling of data underscores the commitment to ethical research practices and compliance with data protection laws. The Dollarama Dataset is organized in a structured tabular format, where each row represents a unique SKU. This structure facilitates straightforward data and analysis. The dataset includes both numerical and categorical variables.

Before the analysis, the dataset underwent several preprocessing steps to ensure data quality and consistency. Missing values were addressed through appropriate imputation methods or, where necessary, the exclusion of incomplete entries. Numerical variables were normalized to ensure that they were on a comparable scale, which is particularly important for machine learning models that can be sensitive to the scale of the input data (Zietsman and van Vuuren, 2023).

4.1.2 Summary Statistics of Key Variables

The summary statistics in the Dollarama Dataset (Table 7) offer a detailed overview of the key variables that are critical to understanding the retail environment. These variables include Purchasing Price, Minimum Order Quantity (MOQ), Gross Margin (GM), Stock Out, and Demand Metrics, each of which provides unique insights into different aspects of the retail supply chain and operations.

Purchasing Price: The average purchasing price of $0.67, with a standard deviation of $0.39, suggests a moderate level of variability in the prices that Dollarama pays to its vendors. This variability is further highlighted by the range of prices, which spans from as low as $0.10 to as high as $2.26. Such a wide range indicates that Dollarama deals with a variety of products or suppliers, each with different pricing strategies. The lower end of the range might represent bulk or low-cost items, while the higher end could indicate premium or specialized products.

Minimum Order Quantity (MOQ): The MOQ has a mean of 8,359.21 units, which, coupled with a significant standard deviation of 9,231.74 units, points to a substantial variation in the minimum order sizes required by different vendors. The range from 0 to 192,312 units underscores the diversity in vendor expectations, with some vendors possibly having very flexible ordering policies (as indicated by a MOQ of 0), while others require large orders. This variation could reflect differences in vendor size, production capacity, or negotiation terms, and it may have implications for inventory management and cash flow planning.

Gross Margin (GM): The Gross Margin, with a mean of 22.09% and a standard deviation of 16.95%, highlights the variability in profitability across different products or categories. The broad range, extending from 0% to an exceptionally high 197.37%, suggests that while some products may be sold at a break-even or even a loss (0% margin), others are generating significant profits. The presence of extremely high margins could indicate luxury or exclusive items, or products with low competition. Understanding this distribution is crucial for making pricing decisions and optimizing product mix to maximize overall profitability.

Stock Out Percentage: The Stock Out percentage has a mean of 11.5%, with a standard deviation of 10.31%, indicating that stock availability issues vary widely across different products. The range from 0% to 50% shows that while some items are always available, others experience frequent stockouts, potentially leading to lost sales and customer dissatisfaction. This variation might be influenced by factors such as supplier reliability, demand forecasting accuracy, and inventory management practices. Analyzing stockout patterns can help Dollarama identify critical areas for improvement in supply chain efficiency and inventory control.

Demand Metrics: The demand metrics, with an average of 9,029.79 units and a standard deviation of 7,690.85 units, reveal a high level of variability in product demand. The range, stretching from 0 to 122,940 units, indicates that some products have negligible demand, while others are in extremely high demand. This wide demand spectrum highlights the importance of demand forecasting and inventory optimization to ensure that high-demand items are sufficiently stocked, while low-demand items do not tie up valuable shelf space or capital.

These summary statistics provide a foundational understanding of the dataset, shedding light on the distributional properties and variability of key retail metrics. This information is not only vital for descriptive analytics, where the goal is to summarize and understand the current state of the business, but also for predictive analytics, where these insights can inform more accurate forecasting models, optimize inventory levels, refine pricing strategies, and ultimately enhance decision-making processes. By thoroughly analyzing these metrics, Dollarama can better navigate the complexities of retail operations, improve profitability, and ensure a more efficient supply chain.

Table 3: Descriptive Statistics of Key Variables

Variable	Mean	Standard Deviation	Min	Max
Purchasing Price (USD)	0.67	0.39	0.10	2.26
MOQ (units)	8,359.21	9,231.74	0	192,312
GM (%)	22.09	16.95	0	197.37
Stock out (%)	11.5	10.31	0	50
Demand Metrics (units)	9029.79	7690.85	0	122,94

Figure 4 presents the data distribution of key variables: purchasing price, demand metrics, Gross Margin (GM), stock level, and Minimum Order Quantity (MOQ), respectively. These distributions provide critical insights into the behavior and characteristics of each variable, helping to understand their underlying patterns and relationships.

The continuous nature of the distributions indicates that the variables take on a range of values rather than discrete categories. This continuity suggests that the variables are measured on a scale that captures fine variations, offering a more detailed view of the data.

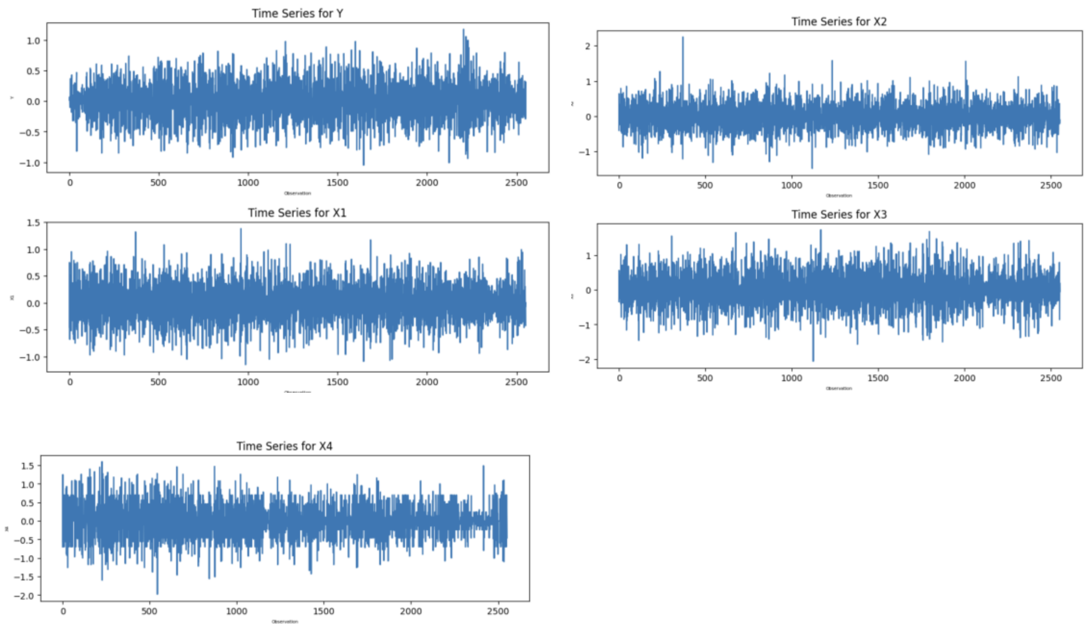


Figure 4: Distribution of Key Variables across Dollarama dataset

3.2 ANALYSIS OF FACTORS AFFECTING PURCHASING PRICE

The study look into the critical factors that influence purchasing prices in the retail sector, focusing on key variables such as Minimum Order Quantity (MOQ), Gross Margin (GM), the number of articles from vendors, and demand metrics. By leveraging regression analysis and machine learning techniques, we aim to understand how these variables impact purchasing prices, thus providing actionable insights for retail businesses.

The impact of Minimum Order Quantity (MOQ) is a crucial factor in determining purchasing prices. Regression analysis and machine learning techniques are utilized to investigate the relationship between MOQ and purchasing prices. This analysis considers factors such as volume discounts and economies of scale, which can significantly affect the price per unit. Typically, higher MOQs are associated with lower unit prices due to bulk purchasing discounts offered by suppliers. This relationship is vital for retailers when negotiating with suppliers, as larger orders can lead to cost savings. The analysis also explores the potential drawbacks of high MOQs, such as increased inventory costs and the risk of overstocking, which can offset the benefits of lower unit prices.

The influence of Gross Margin (GM) on purchasing prices is another critical aspect explored in this analysis. The analysis examines how different GM targets set by retailers influence their purchasing prices. Higher GM targets often lead to higher purchasing prices, as retailers aim to achieve a specific profit margin on each product. This relationship is analyzed through regression and machine learning models to understand how GM objectives drive pricing negotiations with suppliers. The study also considers how fluctuations in GM targets, due to factors such as market conditions and competitive pressures, impact purchasing decisions (Rahman et al., 2024).

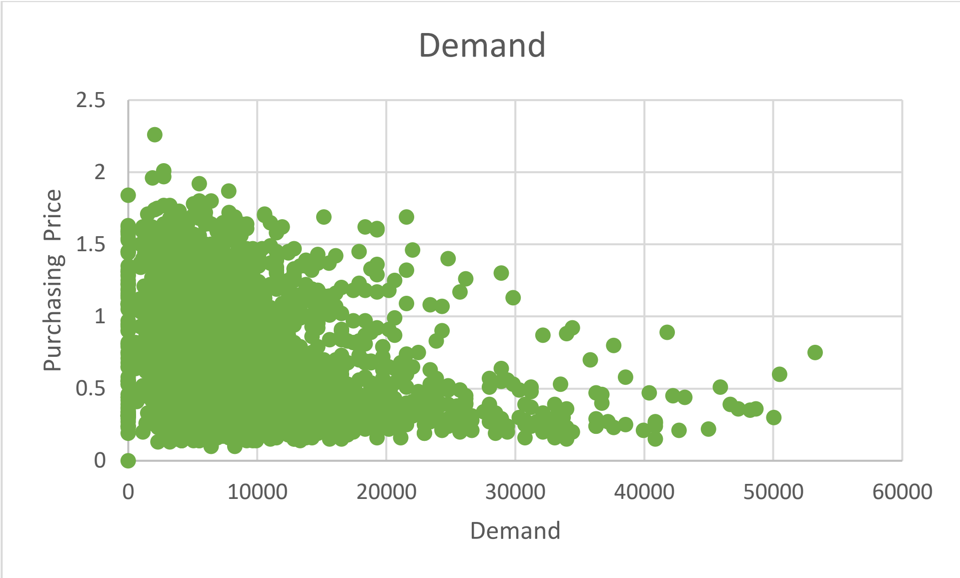


Figure 5: Demand vs. Purchasing Price

Figure 5 is showing the relationship between Purchasing Price and Demand reveals a clear pattern: as the purchasing price increases, the number of data points representing demand decreases. This indicates that higher prices are associated with lower demand, a trend often seen in retail environments where consumers are price sensitive.

Most of the demand points are concentrated in the lower section of the graph, especially as prices rise. This suggests that when prices are higher, the demand for those products tends to be lower. This distribution highlights the inverse relationship between price and demand, where consumers are likely less willing to purchase items as their prices increase, resulting in fewer sales. This trend is consistent with the economic principle of price elasticity, where demand decreases as prices go up, particularly in a market that caters to cost-conscious shoppers, such as Dollarama. The data suggests that the retailer's strategy of offering lower-priced items aligns with higher demand, while higher-priced items see significantly less consumer interest.

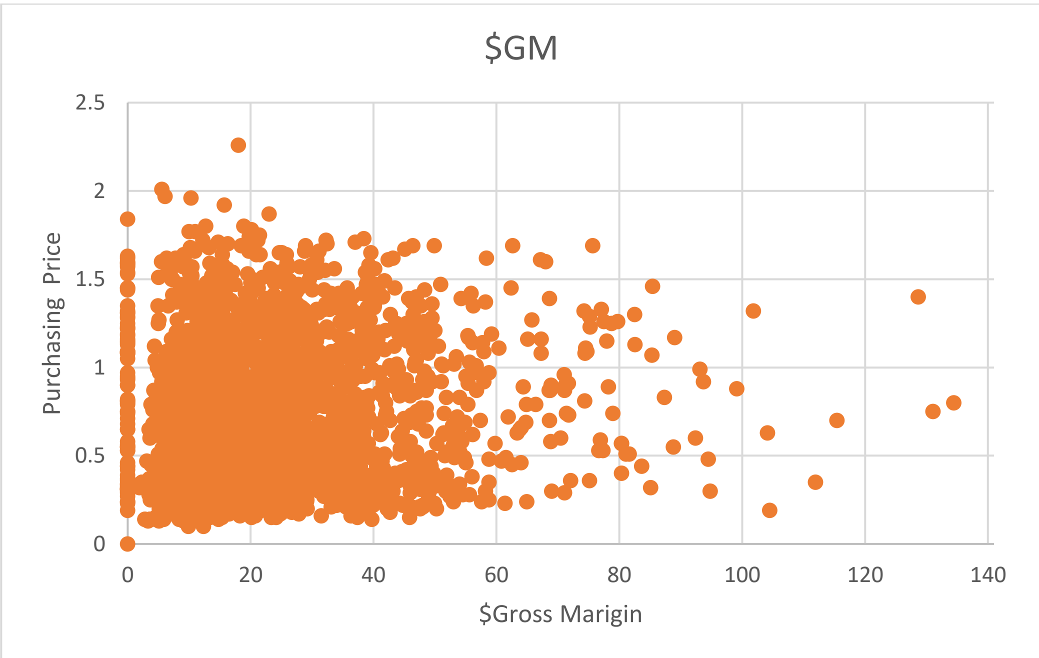


Figure 6: Gross Margin vs. Purchasing Price

Figure 6 illustrates the relationship between Gross Margin (GM) and Purchasing Price. The concentration of data in the lower section of the graph indicates that purchase prices are generally low, suggesting that Dollarama primarily sources lower-cost items, consistent with its strategy of offering budget-friendly products. Despite these low purchase prices, the GM values vary widely, indicating that Dollarama can achieve different profit margins even with similar purchasing costs. This variability may be attributed to differences in product categories, consumer demand, or pricing power.

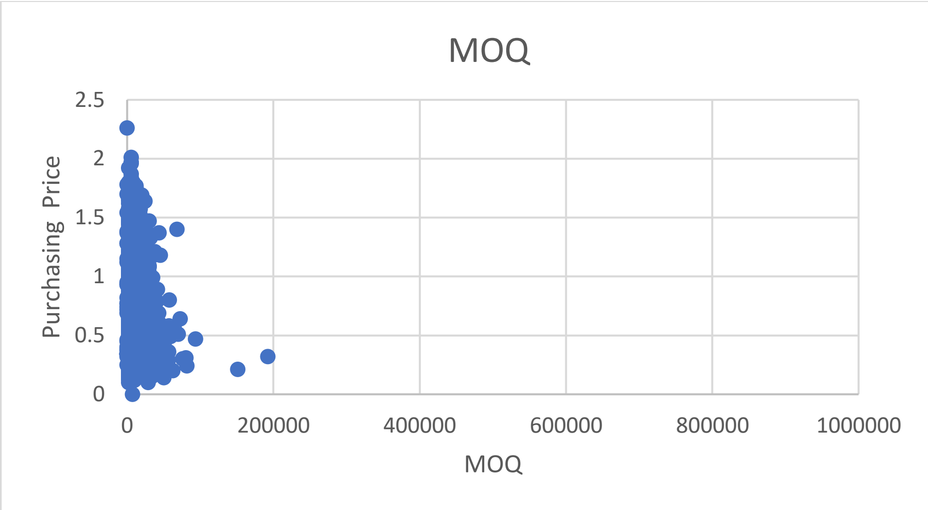


Figure 7: MOQ vs. Purchasing Price

Figure 7 illustrating the relationship between Purchasing Price and Minimum Order Quantity (MOQ) shows that most of the highest MOQs are concentrated within the lowest price range. This suggests that vendors often require larger order quantities when offering products at lower prices. This pattern aligns with typical bulk purchasing strategies, where lower prices are offered in exchange for committing to larger order volumes.

However, beyond this observation, the graph does not display a clear, consistent pattern connecting MOQ and Purchasing Price across the entire dataset. The data points appear scattered without a strong linear or obvious relationship, indicating that MOQ requirements do not uniformly increase or decrease with changes in purchasing price.

Interestingly, a significant cluster of data points seems to hover around the 10,000 MOQ range, regardless of the purchasing price. This could imply that many vendors set a standard MOQ around 10,000 units, independent of the product's cost. This concentration might reflect a common industry practice or a threshold that vendors consider optimal for balancing their pricing and production efficiency. Overall, the graph suggests some relationship between lower prices and higher MOQs but highlights that other factors might also influence MOQ, leading to a less predictable distribution.

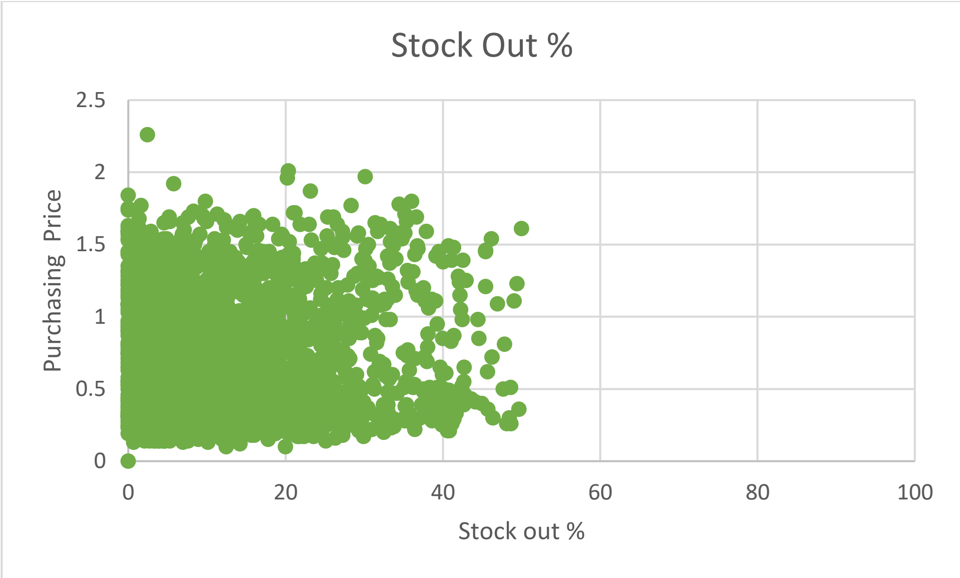


Figure 8: Stock Level Vs. Purchasing Price

The graph on Figure 8, depicting the relationship between Purchasing Price and Stock Out Level shows that there is no clear or consistent distribution pattern. This lack of a distinct trend suggests that stock out levels do not directly correlate with the purchasing price of products in a straightforward manner. Instead, other factors might be influencing stock levels, making it difficult to discern a direct relationship between these two variables.

However, one noticeable feature is that the stock out levels are consistently below 50%. This indicates that, regardless of the purchasing price, the likelihood of products experiencing a stock out is generally moderate to low. This could reflect effective inventory management practices where Dollarama ensures that most products remain adequately stocked, even at different price points.

The absence of a clear pattern in the distribution suggests that factors other than purchasing price such as product demand, supply chain reliability, or inventory turnover rates might play a more significant role in determining stock out levels. This complexity underscores the multifaceted nature of inventory management, where price is just one of many variables affecting stock availability.

Additionally, the product lifecycle stage, whether a product is in the introduction, growth, maturity, or decline phase, plays a significant role in determining pricing strategies. Products in the growth phase may see higher purchasing prices due to rising demand, while those in the decline phase might experience price reductions as retailers seek to clear out inventory (Kotler, 2016).

By conducting a comprehensive analysis of the Dollarama Dataset and exploring these key factors affecting purchasing prices, this chapter provides valuable insights into the dynamics of retail pricing. The findings contribute to the development of predictive models for estimating purchasing prices and offer practical guidance for pricing strategies and procurement decisions in retail businesses.

These insights can inform pricing strategies, enhance negotiation leverage, and optimize inventory management, ultimately aiding retailers in refining procurement strategies and boosting profitability. In the next chapter, Chapter 5, we will detail the Ordinary Least Squares (OLS) regression analysis.

CHAPTER 5
OLS REGRESSION

5.1 OLS REGRESSION RESULTS

Ordinary Least Squares (OLS) regression relies on several key assumptions to ensure the validity and reliability of the model's estimates. Among the most fundamental of these is the assumption of a linear relationship between the dependent variable, in this case, purchasing price and the selected explanatory variables. To evaluate whether this assumption holds, an initial exploratory data analysis was conducted using scatter plots to visually inspect the nature of the relationships between purchasing price and each independent variable: X1 (Gross Margin), X2 (Demand), X3 (Stock Level), and X4 (MOQ).

The graphical analysis suggested distinct patterns. A clear upward linear trend was observed between gross margin and purchasing price, supporting the hypothesis that as gross margin requirements increase, the price at which goods are procured also tends to rise. This is consistent with the idea that higher gross margin targets may pressure buyers to select more expensive products or accept higher procurement costs to maintain profitability targets. Conversely, the scatter plot for demand showed a downward linear pattern, indicating that increased demand tends to be associated with lower purchasing prices. This could suggest economies of scale or supplier incentives during high-demand periods. The relationship between stock level and purchasing price was less definitive; while there was no strong linear trend, a slightly upward tendency was noticeable, potentially hinting at modest price increases during periods of low stock, possibly due to urgency or supply constraints. Lastly, the plot for MOQ (Minimum Order Quantity) showed a slight downward trend, though the pattern was not as pronounced. This may reflect cost advantages associated with ordering in larger quantities, though further analysis was necessary to validate this observation.

Table 4: Graphical Analysis- Linear Relationship

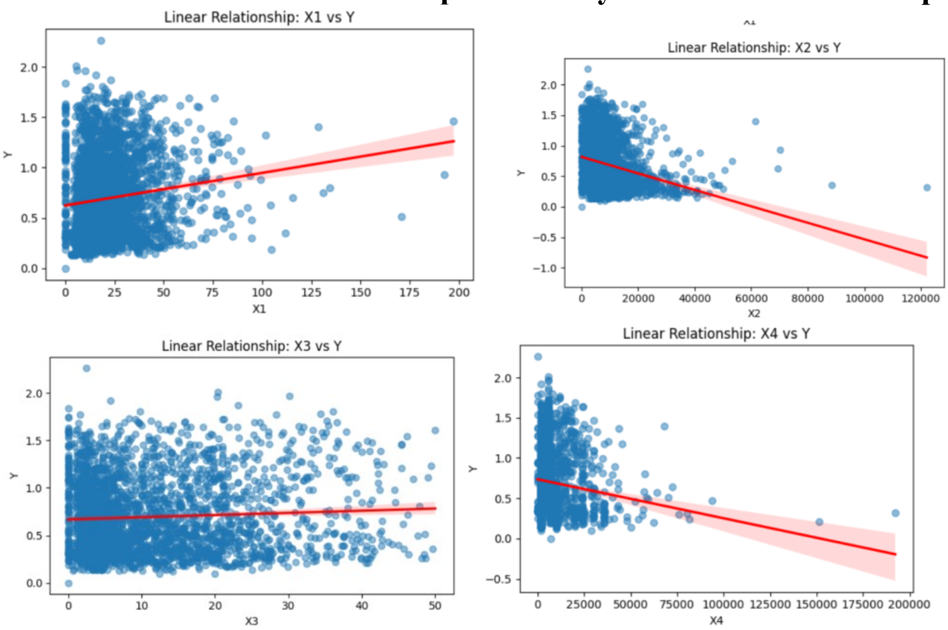
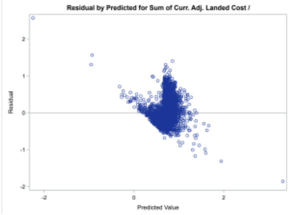
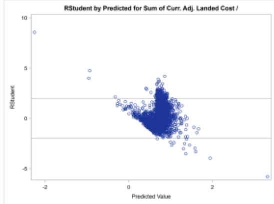
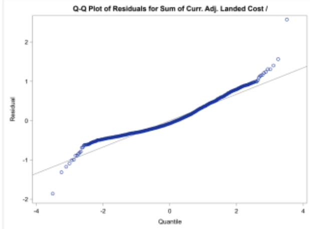


Table 5: Regression Assumption test 1

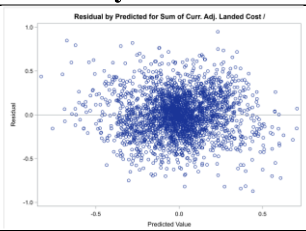
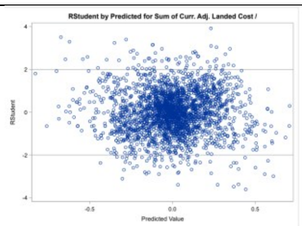
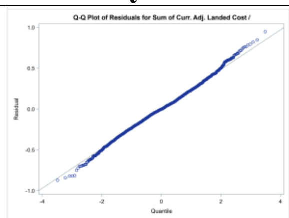
Linearity	constat variants	Normality test
		

Before proceeding with Ordinary Least Squares (OLS) regression, it was essential to assess whether the underlying assumptions of the linear model were met. These include the assumptions of normality of residuals, linearity between the dependent and independent variables, and homoscedasticity (constant variance of residuals). Violations of these assumptions can lead to biased or inefficient estimates, potentially compromising the validity of the model's results.

Initial diagnostic checks were conducted using graphical methods. As shown in Table 5, the Q-Q plot revealed that most residuals fell within ±2 standard deviations of the theoretical normal distribution line, indicating that the assumption of normality was reasonably satisfied. However, a closer inspection of the residual plots suggested issues with linearity and homoscedasticity. Specifically, the residuals were tightly clustered in the center and not randomly distributed across the range of fitted values. Additionally, the residuals were not evenly scattered around the zero line, suggesting non-constant variance(i.e., heteroscedasticity). These patterns imply that the original form of the data might not adequately capture the linear relationships required for OLS regression.

To correct these violations, a logarithmic transformation was applied to both the dependent variable (purchasing price) and the independent variables (gross margin, demand, stock level, and MOQ). Log transformation is a common method in regression analysis to stabilize variance, reduce skewness, and linearize multiplicative relationships. After the transformation, a second set of assumption tests was conducted, summarized in Assumption Test 2 and illustrated in Table 5. The transformed data met all necessary conditions: the residuals were now approximately normally distributed, the residuals vs. fitted plots displayed random scatter indicating improved linearity, and variance across fitted values was much more consistent, confirming homoscedasticity.

Table 6: Regression Assumption test 2

Linearity	constat variants	Normality test
		

To further validate the appropriateness of using the transformed variables in the OLS model, a lack-of-fit test was also performed. This test is particularly useful to determine whether a linear model is suitable for the data. The lack-of-fit test compares the fit of the full model (including all explanatory variables and possible interactions) with a reduced model to assess whether there is a statistically significant improvement in fit. In this case, the p-value was less than 0.05, which indicates that the full model fits significantly better than a reduced model and that lack of fit is present in the untransformed linear model. This result further supported the decision to proceed with the log-transformed model, as it provided a better representation of the data's underlying structure.

Table 7: Lack of fit test

	Df_Resid	SSR	df_diff	ss-diff	F	Pr(>F)
0	2785	314.56	0	NaN	NaN	NaN
1	77	6.48	2708	308.08	1.35	0.044

After confirming that all key assumptions of linear regression were met including linearity, normality of residuals, and homoscedasticity the Ordinary Least Squares (OLS) regression was applied to the log-transformed dataset to examine the relationship between purchasing prices and the selected independent variables: Minimum Order Quantity (MOQ), Gross Margin (GM), stock level, and demand metrics. The use of transformed data ensured that the statistical inferences drawn from the model would be valid and robust, given the previously identified assumption violations in the untransformed model.

The OLS regression was employed as a method for quantifying the strength and direction of the relationships between the dependent and independent variables. This approach allowed for the identification of variables that have a statistically significant influence on purchasing price, providing insight into key cost drivers in the retail procurement process. Significance was assessed using p-values, where variables with a p-value less than 0.05 were considered to have a statistically meaningful impact on the outcome variable.

Model performance and explanatory power were evaluated using both the coefficient of determination (R^2) and the adjusted R^2. While R^2 measures the proportion of the variance in purchasing price explained by the model, adjusted R^2 accounts for the number of predictors included, providing a more reliable measure when comparing models with multiple variables. The results revealed which factors had the most substantial impact on purchasing prices, and how well the model captured the variance in the dependent variable.

By employing OLS regression on the log-transformed data, the study was able to derive interpretable coefficients that reflect multiplicative effects between the variables—a key advantage of using a log-log model in economic and pricing analyses. This modeling approach not only strengthened the statistical validity of the findings but also enabled a more nuanced understanding of how procurement-related variables interact to influence purchasing costs within a low-cost retail context.

5.2 MODEL SIGNIFICANCY AND COEFFICIENTS

The OLS regression was conducted on log-transformed variables, meaning the estimated coefficients are interpreted as elasticities—that is, they represent the percentage change in the dependent variable (purchasing price) associated with a 1% change in an independent variable, holding all else constant. This elasticity-based interpretation provides a more intuitive understanding of proportional relationships in retail economics, particularly when evaluating how operational factors scale with purchasing costs.

The model itself demonstrates strong statistical significance, as evidenced by an F-statistic of 269.73 ($p < 0.0001$), indicating that the group of predictors collectively explains a meaningful portion of the variation in purchasing price. However, the R-squared value of 0.2792 suggests that approximately 28% of the variation in purchasing prices is explained by the included variables, Gross Margin, Demand, Stock Out Level, and Minimum Order Quantity (MOQ). While this highlights the explanatory power of these variables, it also implies that a substantial portion of price variability may be attributed to other external or unmeasured factors, such as supplier negotiations, macroeconomic trends, or category-specific dynamics.

Table 6: OLS Regression output

F value	269.73	**Pr > F**	< 0.0001		
R-Square	0.2792				
Adj R-Sq	0.2782				
Variable	**DF**	**Parameter Estimate**	**Standard Error**	**t-value**	**Pr > /t/**
Intercept	1	0.66417	0.01279	51.92	< 0.0001
Gross Margin	1	0.01481	0.0005277	28.07	< 0.0001
Demand	1	-0.000038	0.0000127	-29.91	< 0.0001
Stock Out Level	1	0.00235	0.000619	3.8	< 0.0002
MOQ	1	0.0000024	0.00000242	3.05	< 0.0023

Examining the elasticity estimates, Gross Margin has the largest positive elasticity (coefficient = 0.0148), meaning a 1% increase in gross margin is associated with a 0.0148% increase in purchasing price. This is consistent with the expectation that higher retailer margin requirements may push vendors to raise their prices. Conversely, Demand exhibits a negative elasticity (coefficient = –0.000038), suggesting that for every 1% increase in average sales volume over the past 12 months, purchasing price decreases by approximately 0.000038%. Although this elasticity appears small in magnitude, it reflects a consistent inverse relationship, potentially explained by economies of scale or increased buyer power at higher volumes.

Stock Out Level has a positive elasticity of 0.00235, indicating that a 1% increase in stockout percentage (relative to expected sales) leads to a 0.00235% increase in purchasing price. This suggests that supply instability or low product availability drives up acquisition costs, possibly due to emergency orders or premium shipping. Similarly, MOQ also shows a positive elasticity of 0.0000024, implying that higher required purchase volumes slightly increase prices. While the effect is modest, it could reflect vendor constraints or inefficiencies associated with large lot sizes.

All variables are statistically significant at the 0.05 level, with t-values well above conventional thresholds, confirming that each elasticity estimate provides a meaningful contribution to the model. Importantly, the use of elasticity-based interpretation in a log-transformed model offers greater insight into how percentage changes in key operational variables influence proportional shifts in purchasing price—an essential consideration for procurement planning, pricing strategy, and supplier negotiations.

In Conclusion, while the model's overall explanatory power is moderate, its elasticity estimates reveal economically and statistically significant relationships between purchasing price and the firm's operational levers. This supports the use of a log-transformed OLS approach for pricing diagnostics in the retail context.

5.3. INTERACTIVE EFFECT

In this study, we aimed to assess the relationship between several predictors, namely gross margin, demand, stock out, and MOQ, and their influence on purchasing price. Initially, a standard Ordinary Least Squares (OLS) regression model was constructed with these four predictors, and the results revealed that stock out and MOQ were statistically significant predictors of purchasing price ($p < 0.05$). This suggested that, when considered in isolation, these variables played important roles in determining purchasing price, alongside gross margin and demand. These findings provided initial insight into the factors that might influence purchasing price decisions.

In real-world data, especially in fields like supply chain, operations, and pricing strategy, the relationship between predictors and outcomes is often not purely additive. This means that the effect of one independent variable on the dependent variable may change depending on the level of another variable. In such cases, simple linear models that only consider the main effects may miss these important conditional relationships. This is where interaction analysis becomes essential.

In the context of this study, we explored how variables such as gross margin, demand, stock out, and MOQ influence purchasing price. Initially, each variable was analyzed under the assumption that its effect on purchasing price was independent of the others. However, this assumption may be overly simplistic. For instance, the impact of stock out on purchasing price might depend on the MOQ. A high MOQ might exacerbate the consequences of a stock-out scenario, or it could buffer it, depending on the purchasing and inventory strategy in place.

By including interaction terms in the model (e.g., stock out × MOQ, gross margin × demand), we allow the regression to capture these conditional effects, where one variable modifies the influence of another. This leads to a more realistic and nuanced model of the system being studied. In business decision-making, this is crucial, because interactions often reflect real trade-offs or synergies between variables that managers or analysts must understand to make informed choices.

Table 7: Interactive OLS output

F value	134.3	**Pr > F**	< 0.0001
R-Square	0.326		
Adj R-Sq	0.323		

	coef	**std err**	**t**	**Pr > /t/**
Intercept	0.75	0.02	39.99	0.000
Gross Margin	0.01	0.00	13.99	0.000
Demand	-4.78	2.49	-19.19	0.000
Stock Out Level	-0.00	0.00	-0.22	0.825
MOQ	2.58	1.73	1.49	0.135
Gross Margin*Demand	1.69	2.75	6.16	0.000
Gross Margin*Stock Out Level	0.00	5.23	4.93	0.000
Gross Margin*MOQ	-1.93	3.63	-5.31	0.000
Demand*Stock Out Level	-2.52	1.34	-1.87	0.000
Demand*MOQ	2.43	2.80	8.68	0.000

Stock Out Level *MOQ	3.04	9.15	-	0.33	0.739

Feature	VIF
Const	9.292
Gross Margin	6.569
Demand	9.688
Stock Out Level	3.678
MOQ	6.705
Gross Margin*Demand	7.622
Gross Margin*Stock Out Level	8.106
Gross Margin*MOQ	12.451
Demand*Stock Out Level	9.085
Demand*MOQ	5.544
Stock Out Level *MOQ	4.627

When interaction terms such as gross margin × demand, stock out level × MOQ, and other pairwise combinations were incorporated into the regression model, a notable shift occurred in the statistical significance of certain variables. Specifically, stock out level and MOQ, which were statistically significant predictors of purchasing price in the initial model, became non-significant ($p > 0.05$) in the interaction model. This change suggests that the interaction terms may be capturing variance previously attributed to the main effects of these variables. It indicates that the relationship between predictors and the outcome variable is not strictly additive, but rather interdependent. The combined effects of variables may better explain purchasing price variability than their individual contributions.

The inclusion of interaction terms inherently increases model complexity, which can lead to the problem of multicollinearity. Multicollinearity arises when predictors, including both main effects and interaction terms, are highly correlated with one another. This correlation can inflate the standard errors of regression coefficients, thereby reduce the precision of the estimates and increase the likelihood of Type II errors. In the present case, the introduction of interaction terms appears to have led to multicollinearity, as evidenced by elevated p-values for previously significant variables. This suggests that multicollinearity may be obscuring the true effects of stock out level and MOQ on purchasing price.

Another plausible explanation for the observed changes in significance is the presence of effect modification. Effect modification occurs when the influence of one predictor variable on the dependent variable varies depending on the level of another predictor. In this context, the impact of stock out level on purchasing price may depend on the level of MOQ, and vice versa. The inclusion of interaction terms allows the model to account for such dependencies, offering a more nuanced representation of the relationships among variables. However, this comes at the cost of reduced clarity in interpreting individual variable effects.

To further investigate these issues, a Variance Inflation Factor (VIF) analysis was conducted. VIF quantifies the extent to which the variance of a regression coefficient is inflated due to multicollinearity with other predictors. The results revealed substantial multicollinearity in the interaction model, particularly among interaction terms such as gross margin × MOQ and demand × stock out level, both of which exhibited VIF values exceeding commonly accepted thresholds. These findings suggest that the stability of the model coefficients may be compromised, and that the inclusion of highly correlated terms could be distorting the interpretation of the results.

While the interaction model resulted in a marginal increase in R^2 (from 0.279 to 0.326), this modest improvement in explanatory power must be evaluated in light of a substantial reduction in the model's F-statistic (from 269.73 to 134.2). The drop in the F-value implies a weaker overall model fit relative to its increased complexity. Furthermore, the loss of statistical significance for stock out level and MOQ, two operationally meaningful variables, raises concerns about the practical utility of the interaction model. If these variables are key drivers in inventory or pricing strategies, the reduced clarity of their effects undermines the value of the model for real-world decision-making.

Moreover, the interpretability of models with multiple interaction terms is inherently more challenging. For researchers and business practitioners alike, a model that provides straightforward, interpretable coefficients is often more useful than one that is only marginally more accurate but substantially more complex. In applied settings, the ability to translate statistical findings into actionable insights is essential.

In conclusion, the inclusion of interaction terms in the regression model introduced multicollinearity, diminished the statistical significance of key predictors, and complicated the interpretation of results. Although there was a slight improvement in model fit as measured by R^2, the costs associated with increased complexity and reduced interpretability outweigh these benefits. The original, more parsimonious model remains preferable, as it provides clearer, more stable, and more actionable insights without compromising predictive performance.

5.4 MULTICOLLINEARITY

Multicollinearity refers to a situation in regression analysis where two or more predictor variables are highly correlated, making it difficult to assess the individual impact of each variable on the dependent variable. When multicollinearity is present, it can cause instability in the estimation of regression coefficients, leading to inflated standard errors and unreliable results. One common method to detect multicollinearity is through the Variance Inflation Factor (VIF), which quantifies how much the variance of a regression coefficient is inflated due to collinearity with other variables. A VIF value greater than 10 is typically considered indicative of problematic multicollinearity, signaling that one or more predictors may need to be removed or combined to reduce redundancy (O'Brien, 2007).

Table 8: Multicollinearity test VIF values

Feature	VIF
Const	7.954475
Purchasing Price	1.387402
Gross Margin	2.536494
Demand	3.120362
Stock Out Level	1.011952
MOQ	1.324515

The Variance Inflation Factor (VIF) values in our dataset provide valuable insights into the degree of multicollinearity among the predictor variables, which is crucial for ensuring the robustness of regression models. Most of the variables, including Purchasing Price, Stock Out Level, and MOQ, have relatively low VIF values, all below 5. This indicates that these variables do not exhibit significant correlation with one another and are suitable for inclusion in the regression model without causing instability or biased estimates. The Gross Margin (GM) and

Demand variables have VIF values of 2.54 and 3.12, respectively, which suggest a moderate level of correlation with other features but still fall within acceptable limits. These values are not high enough to pose significant multicollinearity concerns and suggest that these factors can be reliably included in the analysis.

The constant term (intercept) has a VIF of 7.95, which is slightly elevated compared to the other variables but is still below the threshold of 10, commonly used to flag serious multicollinearity. Since the constant term represents the baseline value rather than a predictor variable, this VIF value typically does not pose a significant issue for model interpretation. Overall, the VIF results indicate that multicollinearity is not a major concern in your dataset, as none of the predictor variables have VIF values above 10, which would suggest problematic correlation. Consequently, the regression model is likely to produce stable, reliable coefficient estimates, with no need to remove or adjust for multicollinearity among the predictors. This reinforces confidence in the validity of the relationships identified between the key factors and the purchasing price.

5.5. POTENTIAL ENDOGENEITY

In any regression model where the goal is to explain or infer causal relationships, it is essential to test for the presence of endogeneity. Endogeneity arises when one or more explanatory variables are correlated with the error term in the regression model, leading to biased and inconsistent coefficient estimates (Wooldridge, 2010). This correlation can result from simultaneity, omitted variable bias, or measurement error. Identifying and addressing endogeneity is particularly important when working with observational data, as is the case in this study, to ensure the validity of the estimated relationships.

There are several potential sources of endogeneity in our model, which aims to explain purchasing price using gross margin, demand, stock out, and MOQ as explanatory variables. For example, it is plausible that purchasing price may influence future gross margins or affect how demand is recorded or forecasted. Similarly, simultaneity or omitted variables (e.g., market shocks, strategic supplier behavior) could influence both the explanatory variables and the outcome, leading to biased estimates if unaccounted for (Stock & Watson, 2020).

To investigate this, we conducted a regression of current purchasing price on the lagged values of the independent variables—specifically, gross margin(t–1), demand(t–1), stock out(t–1), and MOQ(t–1). This method serves as a preliminary diagnostic to assess potential dynamic relationships, i.e., whether past values of the predictors significantly affect the current outcome. If lagged variables are significant, it suggests temporal dependence and may indicate the need for dynamic modeling to account for causality over time (Baltagi, 2011).

The regression results showed that all four lagged predictors were statistically significant at the 5% level ($p < .05$). This implies that previous period values of gross margin, demand, stock out, and MOQ have a meaningful effect on the current purchasing price. For instance, a stock out or a high MOQ in the prior period may cause urgency in procurement, raising prices due to limited supply or less favorable negotiation conditions. Similarly, a strong gross margin in the previous period might influence purchasing leverage or supplier expectations, thereby affecting price outcomes.

These results have two critical implications. First, they confirm that past operational and financial conditions have a lasting impact on pricing decisions, which underscores the dynamic nature of purchasing behavior. Second, they raise the concern of endogeneity, particularly if current or past purchasing prices influence the values of the independent variables, or if both are driven by unobserved common factors. Without addressing this issue, estimates may be biased and policy or managerial interpretations potentially flawed (Angrist & Pischke, 2009).

To model such dynamic interdependencies more appropriately, future research could adopt dynamic econometric models, such as distributed lag models, autoregressive distributed lag (ARDL) models, or vector autoregression (VAR). These approaches allow for the inclusion of lagged dependent and independent variables, capturing both short-term dynamics and long-run equilibrium relationships (Pesaran & Shin, 1999; Lütkepohl, 2005). In addition, models such as dynamic panel data estimators (e.g., Arellano-Bond) are well-suited to controlling for unobserved heterogeneity and address endogeneity using internal instruments (Arellano & Bond, 1991).

However, dynamic modeling is outside the scope of the present study. The current analysis is limited to identifying initial signals of time-dependent effects by using lagged predictors in a static regression model. Nonetheless, the significant influence of lagged variables suggests that future research could benefit from incorporating dynamic modeling techniques to provide a more comprehensive and causally robust understanding of how purchasing prices are shaped over time.

Table 9: Multicollinearity test VIF values

	coef	std err	t	Pr > /t/
Const	0.68	0.02	46.11	0.000
Gross Margin_Lag 1	0.00	0.00	7.32	0.000
Demand_Lag 1	- 1.45	1.47	9.92	0.000
Stock Out Level_Lag 1	0.00	0.00	4.16	0.000
MOQ_Lag 1	1.65	9.13	1.81	0.041

CHAPTER 6
DISCUSSION

6.1 SUMMARY OF FINDINGS

Ordinary Least Squares (OLS) regression emerged as a reliable and interpretable model, demonstrating statistical significance in identifying the key factors that influence purchasing prices. The model explains approximately 28% of the variation in purchasing prices, indicating that while a substantial portion of pricing dynamics is captured, other external or unmeasured factors may also play a role. Variance Inflation Factor (VIF) analysis revealed that most independent variables, such as Purchasing Price, Stock Out Level, and Minimum Order Quantity (MOQ), are not strongly correlated with one another, suggesting that multicollinearity is not a major concern and that the model's predictions are stable and trustworthy. Although Gross Margin and Demand showed moderate correlation with some variables, their VIF values remained within acceptable limits, and their contributions to the regression were both meaningful and interpretable. The intercept term exhibited a slightly higher VIF, but this did not significantly affect the model's overall stability or interpretability. Overall, multicollinearity was not found to be problematic, reinforcing the reliability and generalizability of the regression results. Importantly, the analysis identified Gross Margin, Demand, Stock Out Level, and MOQ as key predictors of purchasing prices. Gross Margin was positively associated with purchasing price, reflecting the impact of desired profit margins, while higher Demand typically led to lower prices through volume efficiencies. In contrast, higher Stock Out Levels and larger MOQs were associated with increased prices, capturing the cost implications of supply shortages and bulk purchasing requirements. Together, these findings support the use of the OLS regression model as a clear and practical framework for understanding how operational and market factors drive retail purchasing prices, thereby enabling more informed decision-making in procurement and pricing strategies.

6.2 IMPACT OF KEY PREDICTORS ON RETAIL PRICE PREDICTION ACCURACY

The primary objective of this study was to examine key factors, Minimum Order Quantity (MOQ), Demand, Stock Levels, and Gross Margin influence purchasing prices in the retail sector. By applying regression analysis, the study aimed to uncover the strength and direction of these relationships, providing actionable insights for procurement and pricing decisions. The results revealed that higher MOQ and Stock Out Levels tend to increase purchasing prices due to supplier constraints and supply-demand imbalances, while higher Demand can lower prices through volume efficiencies. Gross Margin requirements, as expected, drive prices upward to maintain target profitability levels.

These findings offer practical value to retail businesses by highlighting the operational levers that directly affect procurement costs. Understanding the influence of these variables allows retailers to refine their strategies such as negotiating more favorable supplier terms, optimizing inventory management to reduce stockouts, and adjusting pricing structures to meet financial goals. The analysis presented here serves as a foundation for more informed, data-driven decision-making in retail purchasing, enabling businesses to improve cost efficiency, enhance supplier relationships, and strengthen overall financial performance.

1. Influence of Minimum Order Quantity (MOQ) on Purchasing Prices

The findings from the regression analysis reveal that Minimum Order Quantity (MOQ) has a positive relationship with purchasing prices, indicating that as the MOQ increases, purchasing prices also tend to rise. This result is consistent with the common business logic that larger order quantities often come with higher procurement costs. Although many retailers may assume that bulk purchasing results in cost savings due to economies of scale, in practice, MOQ requirements can lead to price premiums under certain conditions. This is often due to supplier pricing policies, which may offer better pricing for larger, bulk orders but still require retailers to pay a premium upfront. Suppliers may set MOQ levels based on their production capacities or inventory management strategies, where larger quantities justify a higher unit price in order to offset fixed costs or ensure consistent supply chains.

The rationale behind this relationship is multifaceted. Suppliers may impose higher prices for larger orders as a way of managing their production or storage costs. For instance, fulfilling large orders may require more complex logistical planning, including specialized packaging, transportation, and storage solutions, which incur additional costs. These added logistical costs are often passed down to the retailer, leading to higher purchasing prices. Moreover, MOQ-based pricing policies could also reflect a strategic decision by suppliers to balance their production schedules and ensure that their factories or warehouses remain at optimal capacity. As a result, even when buying in bulk, the economies of scale that retailers expect may be partially offset by the logistical and administrative complexities associated with managing large orders.

For retailers, this relationship between MOQ and purchasing prices poses a trade-off. On one hand, larger orders may offer discounts per unit if the supplier provides favorable terms for bulk purchasing. On the other hand, higher MOQs often come with higher upfront costs, as the retailer is committing to a larger quantity of inventory than they may need at that moment. Therefore, retailers must carefully evaluate whether the cost savings from bulk purchasing truly justify the higher initial investment required to meet the MOQ. This evaluation often depends on the retailer's ability to manage inventory effectively, anticipate future demand, and balance their immediate purchasing costs with their long-term sales projections.

In practice, retailers may need to adjust their procurement strategies to ensure that the potential benefits of larger orders are not outweighed by the negative effects of higher prices and excess inventory. One option could be to negotiate better terms with suppliers, such as securing discounts based on volume or gaining flexibility in MOQ requirements. By discussing terms with suppliers, retailers may be able to reach an agreement that balances both price advantages and supply chain constraints, ensuring that they are not overburdened by unnecessary stock or inflated prices. For example, retailers could negotiate smaller MOQs to avoid locking in excess inventory that might not turn over quickly enough to justify the price premium. Additionally, forward buying (purchasing inventory in advance) could be considered, but only when demand forecasting supports the volume, helping to prevent overstocking and tying up working capital.

Moreover, inventory management strategies play a key role in mitigating the risks of high MOQ-related prices. Retailers could employ techniques such as just-in-time inventory or demand forecasting to minimize the need for large quantities of stock while still maintaining sufficient inventory levels. Demand forecasting tools can help retailers anticipate future sales patterns and order just enough stock to meet the forecasted demand, thus reducing the need to buy excessive quantities and incur higher procurement costs. By employing more dynamic procurement strategies, retailers can avoid the risks associated with excessive purchasing volumes while still leveraging the benefits of bulk buying when it aligns with market conditions.

In conclusion, the positive relationship between MOQ and purchasing prices suggests that retailers need to carefully consider the trade-offs involved in bulk purchasing. While large orders can sometimes offer cost savings, the associated price premiums due to logistical and supplier costs must be weighed against the retailer's inventory needs, cash flow constraints, and market demand. Retailers can adopt more flexible procurement strategies, negotiate better terms with suppliers, and leverage inventory management techniques to optimize their purchasing decisions and reduce the negative impact of high MOQs on purchasing prices. By doing so, they can ensure that the benefits of bulk purchasing align with their overall supply chain efficiency and profitability goals.

2. Impact of Demand Fluctuations on Purchasing Prices

The analysis also revealed that demand has a negative relationship with purchasing prices, indicating that as demand for a product increases, purchasing prices tend to decrease. This result might initially seem counterintuitive, especially since high demand is typically associated with price increases in many markets. However, this finding can be explained through several key factors such as economies of scale and competitive market dynamics. As demand rises, retailers may place larger orders or increase the volume of their purchases from suppliers, leading to bulk purchasing advantages. Economies of scale occur when the cost per unit decreases as the volume of goods ordered increases, allowing suppliers to offer discounts or better pricing terms for larger purchases. This behavior can result in lower purchasing prices despite the higher demand, as suppliers are motivated to offer competitive prices to secure larger, repeat orders.

Additionally, the negative relationship between demand and purchasing prices can also reflect broader competitive market dynamics. In industries with numerous suppliers or intense competition, higher demand can prompt suppliers to offer incentives or discounts to win the business of retailers, knowing that they stand to benefit from long-term, high-volume relationships. These discounts help mitigate the impact of increased demand on purchasing prices, ensuring that retailers can keep costs down even as they ramp up orders to meet consumer needs. Suppliers may also offer early payment discounts, volume-based rebates, or flexible delivery terms as part of the negotiations when retailers agree to purchase in larger quantities during periods of high demand.

However, it's important to recognize that this negative relationship in the context of a low-price retail chain like Dollarama is not necessarily indicative of true price elasticity, where a decrease in price typically leads to increased demand. Rather, in the case of Dollarama, lower prices tend to drive higher demand, which is a characteristic of the low-price retail model. This suggests that lower purchasing prices enable retailers to maintain or increase demand without necessarily engaging in price reductions driven by market conditions. This type of pricing strategy helps ensure that higher demand results from low prices, rather than the traditional demand-price elasticity mechanism where price fluctuations influence consumer behavior in a more conventional supply-demand manner.

In response to these demand fluctuations, retailers, especially those like Dollarama, can adjust their procurement strategies to optimize purchasing costs. When demand is high, retailers can strategically increase their stock purchases to take advantage of the lower prices offered by suppliers during bulk ordering. By doing so, they can capitalize on lower unit prices, securing inventory at a discount while ensuring they are well-stocked to meet consumer demand. This strategy is particularly beneficial during peak seasons or times of expected demand surges, such as holidays or special promotions, when suppliers are more likely to offer discounts to secure larger orders.

Conversely, during low demand periods, retailers need to be more cautious about their purchasing decisions. Scaling back orders during times of reduced demand helps avoid overstocking, which may tie up capital in unsold inventory and increase storage costs. In such cases, retailers may negotiate smaller, more frequent orders to keep purchasing prices in check while still meeting the minimum requirements for stock availability. By adjusting procurement volumes in response to demand fluctuations, retailers can better manage their working capital, optimize inventory turnover, and minimize the risk of carrying obsolete stock that could result in price markdowns or losses.

Furthermore, retailers can incorporate forecasting models and demand planning tools to improve their ability to predict demand fluctuations and adjust procurement strategies accordingly. By utilizing advanced analytics to estimate future demand based on historical sales data, seasonality, and market trends, retailers can fine-tune their purchasing decisions to ensure they are buying the right amount of stock at the best possible prices. This proactive approach can help retailers secure lower purchasing costs during high-demand periods while preventing the overstocking risks associated with low-demand periods.

In conclusion, the negative relationship between demand and purchasing prices presents retailers with valuable opportunities to leverage market dynamics and economies of scale to optimize procurement costs. For low-price retailers like Dollarama, the lower purchasing prices driven by higher demand can lead to increased sales volumes without the need for true price elasticity. By strategically adjusting their purchasing volumes in response to demand fluctuations, retailers can secure better prices, improve profit margins, and ensure that their inventory management aligns with consumer demand. This dynamic, adaptive approach to procurement helps retailers remain competitive in the marketplace while maintaining cost control.

3. Influence of Stock Levels on Purchasing Prices

Stock levels, and in particular stockout levels, were found to have a positive effect on purchasing prices in the study. This indicates that when retailers experience stockouts—situations where they run out of stock or experience supply shortages—purchasing prices tend to rise due to the scarcity of goods. Scarcity creates upward pressure on prices as suppliers take advantage of the urgent need to replenish inventory. In the absence of sufficient stock, retailers may be forced to accept higher procurement costs to quickly restock their shelves, often opting for expedited shipping or sourcing from higher-cost suppliers who can meet the immediate demand. This effect is particularly pronounced in industries where lead times are long, and replenishing stock can be time-consuming or difficult due to seasonal demand fluctuations or supply chain disruptions.

The relationship between stockouts and increased purchasing prices underscores the critical importance of effective inventory management for retailers. Retailers who experience frequent stockouts face not only increased procurement costs but also potential losses in sales and customer satisfaction. Therefore, avoiding stockouts through effective inventory management is key to controlling purchasing prices and maintaining profitability. Retailers that can keep stock levels steady, avoiding periods of stockout, are more likely to maintain stable procurement prices and avoid the price hikes associated with emergency restocking.

One of the strategies that can mitigate the impact of stockouts on purchasing prices is just-in-time (JIT) inventory management, which involves closely aligning the timing of inventory arrivals with demand to minimize excess stock and reduce the risk of stockouts. By using predictive analytics and leveraging demand forecasting, retailers can accurately anticipate future needs, adjusting their inventory levels ahead of time to avoid shortages. With better forecasting, retailers can order stock earlier, ensuring they don't face the pressures of last-minute reordering, which often results in higher purchasing prices. Furthermore, predictive ordering helps retailers optimize their stock levels by making informed decisions based on expected future demand, seasonal fluctuations, or historical sales trends, ensuring they only order what is needed, when it's needed.

Retailers who excel in managing stock levels efficiently are better positioned to avoid the urgency that leads to higher purchasing prices. In addition, they can negotiate more favorable purchasing terms with suppliers, as they can commit to more predictable, bulk orders that are beneficial to both parties. Suppliers are often more willing to offer competitive prices to retailers who can demonstrate reliable, steady demand for their products. Moreover, retailers with efficient inventory systems can take advantage of bulk purchasing or longer lead times, which can result in lower per-unit purchasing prices.

In conclusion, effective inventory management—whether through JIT, predictive ordering, or demand forecasting—can significantly impact purchasing prices. By maintaining optimal stock levels, retailers can minimize stockouts and avoid paying premium prices in urgent situations. This not only helps in controlling procurement costs but also strengthens the retailer's negotiating position with suppliers, allowing them to secure better pricing terms and improve their overall profitability

4. Impact of Gross Margin Requirements on Purchasing Prices

The OLS results reveal a significant positive relationship between gross margin and purchasing price, underscoring that gross margin directly influences purchasing prices. This finding is particularly notable for a retailer like Dollarama, where maintaining low prices is a central component of its value-oriented business model. The positive relationship between gross margin and purchasing price indicates that, as gross margin requirements increase, purchasing prices also tend to rise. This suggests that retailers must adjust their procurement costs in line with their profitability goals. Higher gross margin targets require higher procurement costs, as retailers may be forced to pay higher prices for goods to ensure the necessary margin. This can occur particularly when certain product categories or suppliers are involved, where costs are inherently higher but are justified by the desired profitability. This dynamic highlight that gross margin is a key determinant in setting procurement prices and influences the entire pricing structure within the retailer's supply chain.

While the direct effect of gross margin on purchasing price is the primary explanation, procurement strategy may also play a role in moderating or exacerbating this relationship. For instance, retailers like Dollarama may engage in procurement practices such as negotiating bulk purchases or fostering long-term relationships with suppliers to mitigate the impact of rising purchasing costs. These strategies can help retailers negotiate better prices, reduce costs in other areas of the supply chain, or offset some of the additional procurement expenses, helping them to still maintain the required margin. However, even with these strategies in place, the core relationship between gross margin and purchasing price remains central, with the necessity of achieving a particular gross margin often dictating the prices at which goods are purchased. The findings suggest that gross margin is not merely an outcome of pricing strategy, but rather a driving factor that shapes the retailer's procurement decisions and cost structure.

Moreover, the results of this study further emphasize that gross margin, along with other key factors such as Minimum Order Quantity (MOQ), demand fluctuations, and stock levels, plays a pivotal role in determining purchasing prices within the retail sector. Each of these factors influences both the final price of goods and the overall procurement strategy. For example, MOQ requirements dictate the minimum amount of product that must be purchased, which can often increase the procurement price due to larger order volumes or less favorable supplier terms. Demand fluctuations also contribute to purchasing price volatility; higher demand can lead to price increases as suppliers raise costs due to limited availability, while lower demand or excess stock may lead to price reductions as suppliers seek to offload surplus inventory. Stock levels have a similar influence low stock levels often drive-up prices due to scarcity, while an overabundance of stock may lead to lower prices as suppliers attempt to clear inventory. The direct impact of gross margin on purchasing prices, therefore, shapes how these other factors are managed, ultimately guiding how retailers negotiate with suppliers, adjust their inventory management practices, and develop strategies to maintain profitability and competitiveness.

By understanding how gross margin directly impacts pricing decisions, retailers can develop more effective procurement strategies that balance cost, profitability, and market competitiveness. For instance, if a retailer knows that higher gross margins lead to higher purchasing prices, they can plan accordingly by adjusting inventory management practices, negotiating more favorable supplier terms, or implementing dynamic pricing models to respond to changes in demand. Additionally, the ability to anticipate the direct effect of gross margin on procurement allows retailers to better prepare for the trade-offs between purchasing cost increases and the potential for increased revenue through higher-margin products. This comprehensive understanding of the factors influencing purchasing prices equips retailers with the knowledge to optimize their supply chain operations and make more informed decisions about how to structure their pricing and procurement processes.

6.3 IMPLICATION FOR RETAIL BUSINESS

The findings of this study offer valuable insights for retail businesses, highlighting key factors that influence purchasing prices and their implications for operational strategies. These factors include Minimum Order Quantity (MOQ), demand fluctuations, stock levels, and gross margin requirements. Understanding how these variables interact is essential for retailers to make informed decisions that affect budgeting, inventory management, and supplier negotiations. For instance, the relationship between MOQ and purchasing price can significantly impact procurement strategies, as larger orders may come with discounts but also increase the overall cost. Similarly, fluctuations in demand require dynamic pricing and inventory management to prevent overstocking or stockouts, both of which can affect profitability.

The results also emphasize the importance of aligning procurement strategies with these key factors. Retailers must adjust their purchasing decisions based on demand forecasts to ensure they maintain an optimal inventory level. For example, a higher stock level in anticipation of increased demand might require adjustments to pricing strategies to ensure profitability. Gross margin requirements should also guide purchasing decisions, as retailers must balance the cost of goods with their desired profit margin. By understanding how these elements shape pricing dynamics, retailers can optimize supplier negotiations, better manage their inventory, and make more accurate financial forecasts.

Given these findings, retail businesses are encouraged to adopt a holistic approach to purchasing and inventory management that incorporates the key factors identified in this study. By doing so, they can enhance their decision-making processes, improve operational efficiency, and ultimately maintain profitability in a competitive marketplace.

6.4. RECOMMENDATION FOR RETAIL BUSINESS

To enhance procurement and pricing strategies, retailers should begin by adopting predictive analytics for pricing and inventory management. Leveraging advanced statistical methods enables more accurate forecasting of purchasing prices, better demand planning, and optimized inventory levels. These improvements support better-informed procurement decisions and contribute to greater operational efficiency. Retailers can further strengthen their pricing approach by leveraging dynamic pricing strategies, which involve using real-time market data, such as consumer demand and competitor pricing, to adjust prices as conditions change. This allows them to stay competitive and profitable while aligning prices with evolving consumer behavior and market trends.

Improving pricing accuracy also involves refining variable selection and integrating additional company- and industry-specific factors into forecasting models. Variables such as customer segmentation, supply chain disruptions, and regional trends add valuable context to pricing decisions, enabling more precise and responsive strategies. To maintain model accuracy over time, it’s important to invest in regular model tuning and continuous improvement. As operational and market conditions evolve, forecasting models must be updated and validated to ensure they continue to support reliable pricing and inventory decisions.

Cross-department collaboration is another essential element. Encouraging close coordination between pricing, supply chain, and data teams ensures that models and decisions are based on a comprehensive understanding of all relevant factors. This collaboration leads to more cohesive strategies and improved alignment across departments.

When designing forecasting models, it is vital to focus on key variables such as Gross Margin (GM), Demand, Minimum Order Quantity (MOQ), and Purchasing Price. These variables provide essential insights into profitability, customer demand patterns, supplier negotiations, and inventory control, all of which are crucial for maximizing operational performance. In contrast, variables like Stock Out Level, while useful for understanding inventory challenges, are less directly tied to pricing or demand forecasting. As such, they should be used cautiously and primarily to inform supply chain improvements rather than pricing decisions.

A well-designed forecasting model should integrate core variables like GM, Demand, and MOQ to achieve greater accuracy in predicting purchasing prices. By refining models to suit inventory characteristics, retailers can align price forecasting with real-world procurement decisions, enhancing both efficiency and profitability.

Finally, while complex models may sometimes offer improved accuracy, there is significant value in focusing on simplicity and interpretability. Straightforward, well-understood models are easier to implement, adjust, and communicate to stakeholders, making them more practical for real-world retail environments where agility and clarity are key to successful execution.

6.5 LIMITATIONS

Despite the promising results obtained from the predictive models in this study, there are several notable limitations that warrant attention. One of the primary concerns is that the performance of the models is not guaranteed to remain consistent across different datasets or under changing market conditions. For example, when applied to new data sources, product categories, or shifts in consumer behavior, the models' predictive accuracy might fluctuate. These variations could be caused by changes in demand patterns, market trends, or purchasing price fluctuations, all of which can significantly affect the reliability of forecasts. This introduces a degree of uncertainty and underscores that model performance is context-dependent, necessitating ongoing validation across diverse datasets to ensure the robustness and generalizability of the findings.

Another important limitation is the restricted access to a broader set of explanatory variables, particularly due to privacy limitations imposed by Dollarama, the retail chain serving as the data source for this study. While the available variables, such as gross margin, demand, stockouts, and MOQ, offered valuable insights into the drivers of purchasing prices, the scope of analysis could not be expanded to include additional potentially relevant factors. These may include variables such as supplier terms, transportation costs, product lifecycle stages, or competitor pricing, all of which could enhance the model’s explanatory power. The inability to access such granular internal or market-sensitive data means that the current models may not capture the full complexity of Dollarama’s procurement and pricing mechanisms. This constraint reflects a broader challenge in retail analytics, where data sensitivity and corporate confidentiality can limit the depth of quantitative analysis.

In addition, the challenge of dealing with outliers and high variability in predictions particularly for high-cost or volatile items presents another limitation. For certain retail categories, such as seasonal or high-value goods, pricing can be significantly influenced by external factors like supply chain disruptions, shifts in consumer preferences, or competitor behavior. These dynamics often result in increased volatility in purchasing prices, making them harder to predict with a high degree of accuracy. Outliers in the data, such as sudden pricing anomalies or abrupt market shifts, can further skew the predictions and reduce overall reliability. As a result, no single predictive model can be considered universally superior. The effectiveness of any model may vary depending on the specific product categories, market conditions, and the stability of pricing data over time.

Moreover, the variability in the accuracy of different models suggests that retailers need to approach predictive pricing with caution. They must consider the nature of their inventory, especially for high-value or volatile items, when selecting and applying forecasting tools. Given the complexity of retail pricing environments, models may need to be fine-tuned for individual product categories or adjusted to suit particular market conditions. Retailers should also consider complementary strategies, such as implementing robust outlier detection, dynamic pricing mechanisms, or scenario-based forecasting to improve the resilience and relevance of pricing decisions, particularly in fast-changing environments.

In conclusion, while the models demonstrated strong potential for forecasting purchasing prices in a low-price retail context, these limitations highlight the need for ongoing model refinement and contextual adaptation. Future studies should aim to address these challenges by incorporating more dynamic datasets—where permitted—exploring enhanced feature engineering techniques and developing more advanced methods for handling data variability and outliers. Additionally, addressing data access restrictions through anonymization or synthetic data generation could offer a path forward for including more explanatory variables, without compromising privacy. Such efforts will be critical to ensure that predictive models remain effective, stable, and actionable over time, especially when applied to real-world retail environments that involve complex, volatile pricing behaviors.

6.6 COMPARING FINDINGS WITH LITERATURE ON RETAIL PRICING STRATEGIES

This study's findings align with key theories in retail pricing. The positive relationship between Minimum Order Quantity (MOQ) and purchasing prices supports the work of Christopher (2016) and Tang (2006), who note that higher MOQs can reduce unit prices but increase holding costs, particularly in situations involving fluctuating demand. This finding highlights the trade-off that retailers face when deciding how much inventory to order—while bulk purchasing can lower unit prices, it requires higher upfront costs and poses a greater risk of excess stock in uncertain market conditions. Furthermore, the negative relationship between demand and purchasing prices aligns with Kembro, Näslund, and Olhager (2017), who argue that demand fluctuations often lead suppliers to adjust prices in response to market forces. Retailers, therefore, need to account for demand patterns and adjust procurement strategies accordingly to avoid paying premium prices during periods of high demand.

Additionally, stockouts were found to drive up purchasing prices, supporting the observations made by Chen (2003) and Mentzer, Stank, and Esper (2008), who emphasize the critical role of inventory management in securing favorable prices. Stockouts not only disrupt sales but also put pressure on retailers to source goods at higher prices to meet customer demand, thereby negatively impacting profitability. The study also affirms the significance of gross margin as a determinant of purchasing prices, in line with Berman and Evans (2013), who argue that retailers must carefully balance their margin goals with procurement costs to maintain financial health. By considering the interplay of these factors, MOQ, demand fluctuations, stockouts, and gross margin, retailers can more effectively manage their purchasing strategies and control costs.

This research contributes to existing literature by providing a comprehensive understanding of the factors influencing retail purchasing prices. The study reaffirms the importance of strategic procurement and inventory management in shaping pricing decisions. Furthermore, it underscores the necessity for retailers to adjust their strategies to accommodate varying market conditions and product characteristics, such as the volatility in demand or supply chain disruptions. As retailers face increasing pressure to optimize profitability while managing costs, the findings of this study offer valuable insights for refining procurement processes and enhancing decision-making.

6.7 FUTURE RESEARCH DIRECTIONS

Future research can build on the findings of this study by addressing several areas that would enhance the predictive accuracy and broader applicability of retail pricing models. One key direction for improvement is the exploration of additional variables or the incorporation of more sophisticated features. Incorporating industry-specific variables or company-specific metrics could offer a deeper understanding of pricing dynamics. For example, while this study focused on general factors like Minimum Order Quantity (MOQ), Gross Margin (GM), stock levels, and demand metrics, additional variables such as pricing elasticity, promotional strategies, customer segmentation, and even real-time competitor pricing data could further refine the models. Industry-specific factors like seasonal demand patterns, supply chain volatility, and geopolitical influences could provide additional layers of context, especially for high-cost predictions. On the company side, factors such as brand positioning, customer loyalty programs, and procurement strategies might play a significant role in shaping pricing decisions, and their inclusion could improve the accuracy of price forecasting for particular retail environments.

In addition to enriching the dataset with new variables, future research should also consider adopting advanced predictive techniques. Machine learning models, such as Support Vector Machines (SVM), Regression Trees, and other non-linear algorithms, offer the potential to capture complex, non-additive relationships among variables that traditional linear models like OLS may not fully capture. These models can better handle interactions, variable importance ranking, and high-dimensional datasets, improving the accuracy of purchasing price predictions. Their ability to adapt to different data patterns also makes them well-suited for forecasting in highly dynamic and competitive retail settings.

Another important avenue for future research is extending the analysis to different datasets and market conditions to validate the models' robustness and generalizability. A more diverse set of retail data would allow for a more thorough evaluation of the model's performance across different product categories, consumer behaviors, and geographical locations. For instance, exploring datasets from industries with highly variable pricing, such as luxury goods, electronics, or fast-moving consumer goods (FMCG), could provide insights into how the models respond to different pricing volatility and demand fluctuations. Additionally, expanding the analysis to different market conditions, such as periods of economic instability, supply chain disruptions, or the introduction of new competitors, could help assess the models' ability to adapt to changing retail environments.

Lastly, focusing on real-world applicability by examining how these models perform in dynamic and rapidly changing retail environments is crucial. Retailers operate in an environment where consumer preferences and market conditions change frequently, often in unpredictable ways. As a result, predictive models should be flexible and able to adjust to new information quickly. Future studies could test how these models perform in dynamic scenarios, such as promotional periods or product launches, and investigate their ability to integrate real-time data feeds for continuous learning. Such approaches would allow retailers to update their models in near-real-time and enhance forecasting precision.

In conclusion, future research should aim to improve existing predictive models by incorporating more relevant and granular variables, adopting advanced machine learning techniques, and validating model performance in diverse and dynamic settings. These improvements will contribute to the development of more accurate, robust, and scalable pricing prediction tools that better reflect the complexity of today’s retail landscape.

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