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# Presenting a Model for Price Discount Strategy in Perishable Products: A Case Study of Fresh Tomatoes

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## Abstract

Agricultural products, are mostly perishable, and ensuring their quality through methods like cold storage or optimal conditions can present significant economic challenges for retailers and small-scale producers. In some cases, these products lose their quality and marketability within a span of less than 24 hours. The main challenge in adopting this strategy is determining the timing and amount of the price discount. To optimize price discounting, four functions need to be estimated: a) a time-dependent quality function, b) a price change function, c) a demand function that is a function of price and quality, and d) an objective function, which is considered here as the retailer's profit function. We employ dynamic pricing models that integrate factors such as quality degradation, inventory levels, and consumer behavior. The research data was collected from three fruit and vegetable stores in Gorgan city. The time period was three months, comprising all working days. Each seller was asked to report the price and quantity of sales on an hourly basis from the beginning to the end of the working day. In this way, about 1000 data were recorded from each store. Tomato was selected as case study due to their widespread consumption, continuous supply, and rapid perishability. The results show that price discounts can significantly enhance profitability while reducing the risk of unsold and wasted products. Specifically, the findings indicate that implementing price discounts every 3 to 4 hours yielded the highest profitability. The average discount is 35%, leading to an 82% increase in gross profit. In contrast, shorter discount intervals (every 1 to 2 hours) with an average discount of 18% improved gross profit by 73%. On the other hand, longer discount intervals (every five to seven hours) with an average discount of 46% resulted in a 66% increase in gross profit. Furthermore, this study further emphasizes how crucial consumer perception is to the effectiveness of dynamic pricing methods. The perception of lower product quality brought on by excessive discounting may have a detrimental effect on long-term store credit and customer trust. Perishable product waste can be reduced through the implementation of price reduction strategies. However, the results indicate that sellers' profits increase in the absence of price reductions. Future research could enhance this framework by incorporating additional factors that influence product quality, such as temperature, humidity, and product variety; examining the effects of consumer price expectations on demand; extending the model to other perishable products, including meat and dairy; and leveraging advanced technologies, such as blockchain and artificial intelligence, to improve dynamic pricing and inventory management.

**Keywords:** Discounts timing, Dynamic pricing, Quality function, Retail markets, Tomato



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## Introduction

Cutting prices has also become a fundamental strategy for modern retailers in their bid to win over customers, boost sales, and gain market competitiveness (Santos & Bacalhau, 2023). For products that are perishable, such as fresh fruits and vegetables, the strategy is even more critical due to their short life, rapid deterioration in quality, and the need to determine prices in a timely manner and control inventory effectively (Wang *et al*., 2022). Unlike non-perishables, perishables cannot be stocked for eternity, and their value is devalued very rapidly with time (Blackburn & Scudder, 2009). Hence, the average retailer will then be forced to rely on dynamic pricing techniques to manage stock, reduce wastage, and maximize returns (Kayikci *et al*., 2022). However, how price discounting is tied to product perceived quality is complex and multifaceted. Whereas discounts can increase demand and stimulate consumption, they would most likely also increase consumers' uncertainty about the quality of products, especially if the magnitude of the discount is intermediate or inopportune (Zheng *et al*., 2022). Unlike non-perishable goods, perishable items cannot be stored indefinitely, and their value rapidly diminishes over time (Blackburn & Scudder, 2009). Consequently, retailers often rely on dynamic pricing strategies to manage inventory, reduce waste, and maximize revenue (Kayikci *et al*., 2022). However, the relationship between price discounts and perceived product quality is complex and multifaceted. While discounts can stimulate demand and encourage purchases, they may also increase consumers' uncertainty about product quality, especially when the discount depth is moderate or poorly timed (Zheng *et al*., 2022).

Consumers are likely to associate deep price cuts with inferior quality, and this adds more ambiguity as well as brand distrust and long-term loyalty loss. This is a very challenging thin line between quality perception and price appeal, especially for retailers who deal in perishable goods where there is high risk and little leeway for mistakes (Zheng *et al*., 2022; Aschemann-Witzel *et al*., 2015).

The importance of effective pricing strategies for perishables is reinforced by the challenges created through quality deterioration and inventory control. Fresh produce such as tomatoes is inherently susceptible to quality deterioration over a period of time and is sensitive to temperature, humidity, handling practices, and storage conditions. Recent studies have shown that efficient temperature management of storage is crucial in maintaining the quality and shelf life of perishable food items (Eze *et al*., 2024).

Retailers need to emphasize effective inventory management to minimize quality deterioration and extend product shelf life. Shelf life—defined as the period during which a perishable product maintains acceptable quality, poses a critical challenge in fresh food supply chains. Recent studies highlight the importance of integrating real-time tracking technologies and predictive analytics to improve shelf-life forecasting and support timely and informed distribution decisions. (Rashvand *et al*., 2025; Mamidala, 2023).

Stores must monitor stock levels closely an d implement practices such as First-Expired-First-Out (FEFO) to sell first the older products before the newer ones. FEFO is highly effective in reducing waste and product quality in the business of perishable items (Reid, 2025).

Moreover, as items approach the end of their life cycle, their perceived value decreases, typically requiring price discounts to generate demand. But price actions must be treated with caution so they do not weaken profit margins and compromise the brand equity. Emerging studies have suggested data-driven dynamic pricing frameworks that optimize markdown strategies for perishable products, balancing sales quantity and profitability (Syed *et al*., 2024). Dynamic pricing approaches are increasingly important for the management of perishable goods in modern retail. Static pricing operates on historic data and restricted information, while dynamic pricing utilizes real-time information, such as shelf life left, stock levels, customer demand, and market conditions, to optimize the best price choices and reduce wastage (Syed *et al.*, 2024; Kayikci *et al*., 2022). This flexibility enables retailers to rapidly respond to shifts in market demand and product availability, enabling real-time price strategy optimization to maximize profitability and reduce wastage (Syed *et al.*, 2024). One of the strongest aspects of dynamic pricing is that it is able to match demand and supply in the best possible manner. In the case of perishables, in which stocks are short and demand is volatile, dynamic pricing minimizes food wastage by selling off excess stock before it goes bad and captures maximum revenue during peak demand. For instance, Kayikci *et al*. (2022) propose a four-step data-driven optimal dynamic bulk fruit pricing policy where real-time IoT sensor data is utilized to reduce food losses in retailers. Along similar lines, Nomura *et al.* (2025) depict the implementation of deep reinforcement learning for computing optimal ordering and pricing policies for perishable inventory so that there is more flexible and intelligent decision-making in extremely volatile retail scenarios. Innovations in data analysis and machine learning further amplified dynamic pricing model feature sets more recently. Retailers nowadays can leverage real-time information from point-of-sale systems, IoT sensors, and customer behavior analytics to make more intelligent and responsive price choices. For example, Wang *et al*. (2024) designed a deep reinforcement learning algorithm that optimizes dynamic prices and inventory management for perishable items with age-dependent probabilistic demand. The study uses evidence from actual sources of information obtained from Gorgan stores in Iran to provide recommendations for retailers who are interested in optimizing price techniques, reducing losses, and enhancing profitability. Previous research highlights the necessity of such techniques in dealing with perishable goods (Salmasnia & Talesh-Kazemi, 2022). This study addresses some primary questions: How do consumer demands for perishable products such as tomatoes respond to price discounts? What is the optimal frequency and amplitude of discounts to minimize waste and achieve maximum profit? How does timeliness of perishability impact price and consumer choices? What is the role of inventory management in making dynamic pricing systems successful for perishables?

Efficient inventory management is crucial as it enables effective monitoring of stock levels and product freshness, enabling timely price adjustment to minimize waste and maximize revenue. By offering solutions to these queries, this study seeks to contribute to the increasing body of literature on dynamic pricing and perishable product management (Zhou *et al*., 2023; Hasiloglu-Ciftciler & Kaya, 2025). The findings are expected to provide operational guidance for retailers so that they can make the best possible price decisions, inventory decisions, and waste reduction decisions (Sasanuma *et al*., 2021; Hua *et al.*, 2021). Finally, this research proves that dynamic pricing can be an effective tool that retailers can use to help mitigate the specific challenges of managing perishable products, resulting in improved profitability and environmentally friendly business practices (Hasiloglu-Ciftciler & Kaya, 2025) waste reduction (Sasanuma *et al*., 2021; Hua *et al*., 2021). Ultimately, this study demonstrates that dynamic pricing can serve as a powerful tool for retailers to navigate the unique challenges of perishable product management, leading to increased profitability and sustainable business practices (Hasiloglu-Ciftciler & Kaya, 2025).

## Methodology

### Data Collection

This study collected empirical data from three retail stores in Gorgan, Iran, over a three-month period in autumn 2023. The dataset focuses on tomatoes—a highly perishable product with a limited shelf life—to examine the relationship between pricing strategies, sales patterns, and inventory control. The stores were randomly selected in an effort to provide a good sample of the local retail market, witnessing diverse consumers' behaviors and operating practices (Herbon *et al.*, 2014).

Data obtained included the following key variables. Daily sum of retail purchases: total amount of tomatoes purchased by shops per day, which represents levels of supply.Erasing the first hourly price of each day in each shop to a base level of 100, the remaining hourly prices are expressed as relative percentages from starting price. This approach facilitates standardized comparison of intra-day price variations between stores and periods and controls for the effects of variation in baseline prices, store-level characteristics, and seasonality.

Hourly sales by retailer: Sales per hour of tomatoes reveal demand patterns and consumer purchasing behaviors.

Hourly prices were tracked to obtain dynamic prices caused by price movements over the day resulting from retailers' price dynamics. To control for the effects of seasonal fluctuation, store-specific price strategy, and base price variation, the initial opening price for each store on every day was assigned a base value of 100. All the later prices were then quantified in terms of percentage deviation from the base. This standardization permitted systematic and comparable investigation of price differences across different stores and periods, irrespective of relative price levels or other extraneous factors such as location or season.

This complete dataset enabled us to study how the price movement affects the sales by the hour, how inventory varies during the day, and how these variables interact with the perishability of tomatoes (Yang *et al.*, 2014). Through the analysis of such variables, this research seeks to find optimal pricing policies that maximize profit while minimizing waste (Ferguson & Katzenberg, 2006).

Adding hourly price and sales data is particularly beneficial in that it enables the study to gauge actual consumer response to price variations in near real-time. This level of accuracy is essential to grasping the shape of fresh product management, where slight movements in price or quality can have significant implications for sales (Herbon *et al.*, 2014). In addition, the dataset provides a robust foundation for the development of predictive models that will inform future dynamic pricing actions Liu *et al.* (2023).

**Model Development**

This study employed a dynamic pricing model specifically designed for perishable products, such as tomatoes. This model integrates the following three key factors:

– Quality degradation: Decline in product quality over time.

– Inventory levels: quantity of products available in the stock.

– Consumer demand: The relationship between price, quality, and purchasing behavior.

The model uses the following key equations.

**Quality Index (U(t))**

Previous studies have shown that the decline in a quality attribute of agricultural products can be approximated by one of four basic mechanisms:

1- Zero-order reactions with linear kinetics,

2- Michaelis-Menten kinetics,

3- First-order reactions with exponential kinetics, and

4- Autocatalytic reactions with logistic kinetics (Khazaeli *et al.*, 2024).

All four methods require laboratory measurements. Each quality feature should be measured separately. In addition, in marketing, quality is related to the perception of buyers, which does not necessarily correspond to laboratory results. According to the above limitations, in this study, the quality was estimated from the perception of product quality through the behavior of buyers. Since the price discount by the seller is due to the buyers' low of acceptance of the supplied quality and price combination of tomato, it is assumed that the price discount is a substitute for the quality of the product. The lower quality, caused the buyers' lower of acceptance and the greater the motivation for a price higher discount by sellers. The reason for choosing the logit function is the form of the decay function, which in all four kinetic models produces a graph similar to the graph of cumulative distribution models such as the logit model.

So the quality index U(t) measures the perceived quality of the product at time t, with values ranging from zero (lowest quality) to one (highest quality). It is defined as:

$$U(t) = Ln\left(\frac{D}{1-D}\right) = f(time) + \epsilon_u \qquad (1)$$

Where D is the average discount applied to the product. In this function, the decay rate is obtained from the following equation:

$$\frac{dD}{dT} = \beta D(1-D)t > 0$$

**Price Change (ΔP(t))**

The price change ΔP(t) at time t is modeled as

$$\Delta P(t) = \beta_0 + \beta_1 P_{t-1} + \beta_2 U_t + \beta_3 Q_t + \epsilon_{\Delta p} \qquad (2)$$

Where: $P_{t-1}$ is the price in the previous period, $U_t$ is the quality index at time t, $Q_t$ is the remaining inventory at time t, $\epsilon_{\Delta p}$ the error term (random disturbance) in the price change equation at time t.

This equation captures how prices change over time, based on previous prices, product quality, and inventory levels. Coefficients $\beta_1$, $\beta_2$, and $\beta_3$ quantify the influence of each factor on price changes (Elmaghraby & Keskinocak, 2003).

**Demand Function $q_t$**

Consumer demand $(t)$ at time t is modeled as:

$$q_t = \gamma_0 + \gamma_1 P_t + \gamma_2 U_t + \gamma_3 t + \gamma_4 t^2 + \epsilon_q \qquad (3)$$

Where $P_t$ is the current price at time t, $U_t$ is the quality index at time t represents the period, $\epsilon_{qt}$ is the error term.

**Discounting as a Key Strategy**

This equation models consumer demand as a function of the price, quality, and time. The inclusion of a quadratic term $t^2$ allows for nonlinear effects of time on demand, such as increased purchasing behavior during peak hours or reduced demand as the product approaches the end of its shelf life This approach aligns with the modeling strategies employed by Macías-López *et al.* (2021), who incorporated time-dependent demand functions to account for shelf-life constraints in perishable goods .Discounting is a key strategy in this study, implemented to deplete inventory and maximize profit before product quality significantly deteriorates. Pricing adjustments were made at specific intervals (hourly, every three, five, or seven hours). Each pricing adjustment balances inventory levels, consumer demand, and quality degradation.

Hourly price fluctuations are modeled as a function of price, quality, and remaining inventory. Here, $P_0$ represents the initial retail price of tomatoes. The sales function $q_1$ can be calculated using the sales quantity $q_1$ and the quality function $u_1$. The remaining product quantity was then determined by subtracting q1 from the total product quantity Q in the first period.

The discount amount arises from price change (ΔP), which is influenced by quality changes (u). This allows for the calculation of the new price point, $P_1$. The remaining product quantity is re-evaluated for the next period ($T_2$) using the same approach. This cycle of calculations is repeated to assess the sales and remaining product quantities in subsequent periods.

The iterative process in Fig.1 enables an analysis of pricing strategies and inventory management based on sales performance and product quality adjustments. Subsequently, the discount function estimation examines the impact of discounts on profit and provides insights for optimization.

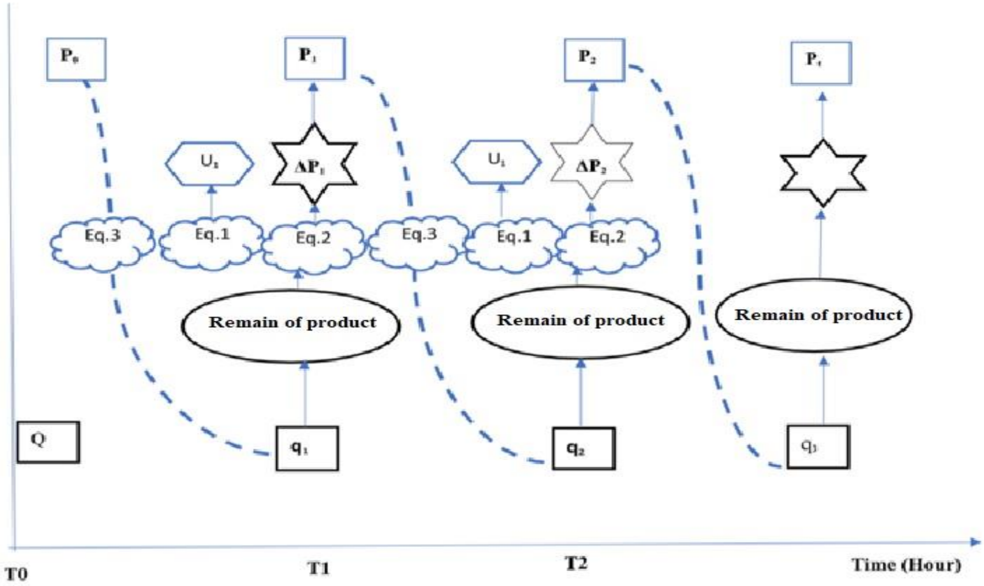


**Figure 1- Iterative Discounting Process (research findings)**

The dynamic pricing model integrates these equations to optimize the pricing strategies for perishable products. By continuously updating prices based on real-time data, the model aims to:

Maximize profit by adjusting prices to balance demand and inventory levels.

Waste is minimized by ensuring that products are sold before their quality degrades significantly.

Enhance consumer satisfaction: Maintain a balance between price attractiveness and perceived quality (Herbon *et al.*, 2014).

**Gross Profit and Net Revenue**

$$GP_T = NR_T = \left(\sum_{t=1}^{T} P_t q_t - P_0 \sum_{t=1}^{T} q'_t\right) - C_0 Q \quad (4)$$

Subject to: $\sum_{t=1}^{T} q'_t \leq Q$

In this equation, GPT and NRT represent gross profit and net revenue for a working day (T), respectively. Pt and P0 are the prices in period t and initial price (without discount), respectively. qt and qt′ represent the demand quantities in period t with and without price discounts, respectively. The term inside parentheses represents the difference in gross revenue (sales value) for a working day (T) with and without price discounts. $C_0$ is the cost of purchasing the product and Q is the total purchase of tomatoes for a working day. This equation is specified considering the inventory constraint. The effectiveness of the model is enhanced by leveraging historical sales and inventory data to inform dynamic pricing decisions in uncertain demand environments (Liu *et al.*, 2023).

## Results

### Current Pricing Patterns in Retail Stores

Before delving into the model estimations, it is essential to understand the current pricing patterns and sales behavior across the three retail stores. Chart 1 illustrates the average pricing trends for tomatoes over a 16-hour sales period segmented by store. Chart 1 reveals several key patterns.

–Price Decline Over Time: In three stores, prices tend to decrease gradually throughout the day. The highest prices are observed in the early hours (e.g., hours 1 to 6), whereas the lowest prices occur in the final hours (e.g., hours 12 to 16). This trend aligns with the perishable nature of tomatoes, where retailers aim to clear inventory before the end of the day to minimize waste.

–Variability in Pricing Strategies: While the overall trend is similar, there are notable differences in pricing strategies among stores.

For instance, store 3 maintains higher prices in the early hours compared to stores 1 and 2, but it also offers deeper discounts in the midday hours.

Discounts and Sales: Discounts are typically applied during mid-day hours (e.g., hours 7 to 12), but their immediate impact on sales is not always evident. For example, in store 1, the highest discount (27%) was offered at hour 10, but the corresponding sales did not show a significant spike. This finding suggests that customer responses to discounts may be delayed or influenced by other factors.

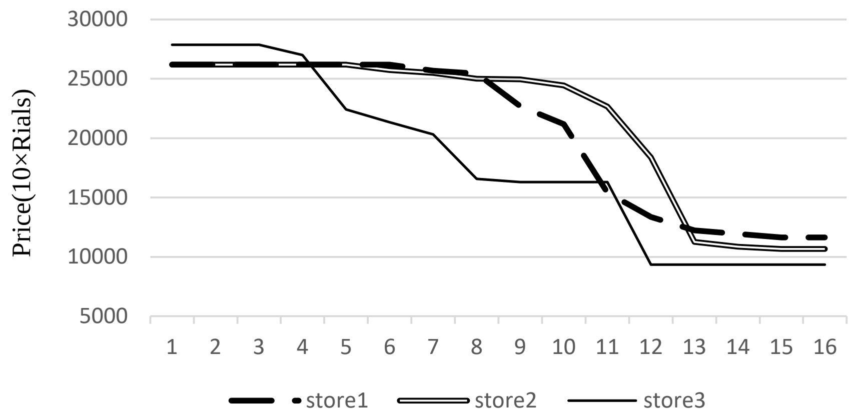


**Chart 1- Average Pricing Trends for Tomatoes across Three Retail Stores (Research Findings)**

These observations highlight the dynamic nature of pricing in the retail environment and underscore the need for a deeper analysis of the factors that drive price changes and their impact on sales.

**Model Estimations**

After examining the current pricing patterns, we now discuss the model estimation results. Table 1 summarizes the key findings of the quality, price changes, and demand functions.

**Quality Degradation over Time**

Chart 2 illustrates the gradual decline in the tomato quality over 24 h. At the beginning of the day, the quality index was high (0.66), indicating fresh, and high-quality tomatoes. However, by the end of the day, the quality index dropped significantly (0.14), emphasizing the importance of timely price adjustments and inventory management to reduce waste and maximize profitability.

The quality equation transforms the average daily discount rate (Δ) into a logarithmic format, enabling the calculation of the probability of a product's quality. The quality index is derived from the discount, where a higher discount is associated with a lower quality index. This ensures that as the discount increases, the perceived quality decreases. The quality function was considered to be dependent on the storage duration of tomatoes, assuming constant environmental conditions. A nonlinear and decreasing relationship between quality and time was obtained. According to the estimation, the effect of each passing hour on the tomato quality depends on the shelf life of the product in the store. Therefore, time has a positive and statistically significant effect on the likelihood of quality degradation. The F-statistic value is 6.73, indicating the overall significance of the model. The RSS was 250, which represented the prediction error of the model.

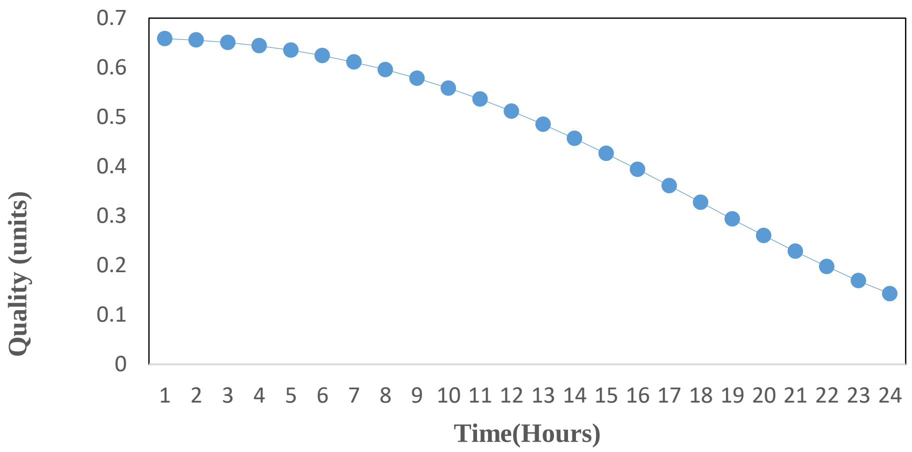


**Chart 2- The Relationship between Quality and Time (24 Hours)**

**Price Change and Demand Dynamics**

The price change function (Table 1) shows that previous prices have a negative and statistically significant effect on current price adjustment. This finding suggests that retailers tend to lower prices in response to higher previous prices, which is likely to stimulate demand and clear inventory. The demand function highlights the relationship between price and sales. The coefficient of 0.27 for the price variable indicates that a 1% increase in price leads to a 0.27% decrease in demand, reflecting the price sensitivity of customers. Additionally, the quality variable had a positive and significant impact on demand, with a coefficient of 10.4. This underscores the importance of maintaining product quality in driving sales. The findings from the model estimations align with the pricing patterns observed in retail stores. The gradual decline in prices over the day, coupled with the significant impact of quality on demand, highlights the challenges retailers face when managing perishable products.

**Table 1- Model estimations**

| Dependent Variable / Independent variable | Quality (unit) | Price Change (%) | Demand (%) |
|---|---|---|---|
| **Constant** | $-0.66^{**}$ (0.14) | $129.8^{**}$ (31.14) | |
| **Time(hour)** | | | $0.27^{**}$ (0.016) |
| **Time$^2$** | 0.004** (0.002) | | $-0.014^{**}$ (0.001) |
| **Price (-1)** | | -0.23 (0.02) | |
| **Quality** | | $-77.34^{*}$ (30.9) | $10.4^{**}$ (0.5) |
| **Non-Sold (%)** | | $-0.59^{**}$ (0.075) | |
| **Price$^{-1}$** | | | $11.5^{**}$ (1.56) |
| **F** | $6.73^{**}$ | $25.6^{**}$ | $53.2^{**}$ |
| **RSS** | 250 | 78937 | 41.51 |
| **Durbin-Watson stat** | | $1.33^{*}$ | $2.38^{**}$ |

Superscripts * and ** denote p<0.05 and p<0.01 respectively
Source: research findings

Although discounts are extensively used in the pursuit of sales, their immediate impact is not always apparent. There may be a need for retailers to pay more attention to the timing and quantity of discounts to maximize their effectiveness. Sharp drops in tomato quality underscore the importance of efficient management of inventories. Retailers should pay attention to strategies that minimize waste, such as dynamic pricing and targeted promotion. Knowing customer price and quality sensitivity is important in determining the best pricing strategy. Retailers can apply data analytics to establish trends in consumer behavior and adjust their pricing strategies in response.

The function for changing price has an intercept (constant) of 129.8, which is the base price when all the variables equal zero. The coefficient for the price of the last period (Price (-1)) is -0.23, meaning that the price change is reduced by a rise in the price of the last period, with a standard error of 0.02. The quality function is -77.34, meaning that the higher the quality, the lower the price changes, with a standard error of 30.9. The coefficient of product not sold (non-sold) is -0.59, indicating

that a rise in product not sold decreases change s in price with a standard error of 0.075. The F-statistic of the model was 25.6, which confirmed the model's significance as a whole, and the Residual Sum of Squares (RSS) was 78,937, which is the prediction error, indicating the explained variation in the dependent variable, which may be due to omitted variables or random shocks. Price does vary over time, calculated from Equation 2, indicating that higher previous prices decrease average discounts and suggesting that more costly tomatoes require lower discounts to sell.

The coefficient of quality index is a measure of a strong negative correlation, where the lower the quality, the higher the discount, in the sense that the more valuable tomatoes are less discounted. The coefficient does not show unsold product, which states that discounts increase as inventory decreases, meaning that discounts are used to accelerate the sales of the remaining amount. The constant term reflects the regular discount when all independent variables are zero. The time coefficient for the demand function is 0.27, which implies that demand increases by 0.27 percent as time elapses, while its standard error is 0.016. The time squared ($Time^2$) coefficient is -0.014, which reflects a non-linear effect in which the increasing rate in demand declines over time, with a standard error of 0.001. The coefficient on quality is -10.4, meaning that decreasing quality increases demand with a standard error of 0.5. The coefficient for the price in the previous period (Price (-1)) is -0.23, indicating prices in the previous period decrease current demand, with a standard error of 0.02. The negative of the inverse price ($Price^{-1}$) coefficient is -11.5, showing that higher prices in a year lower demand in the year at hand, with a standard error of 1.56. The F-statistic for the model was 53.2, confirming the model's significance as a whole, and the Residual Sum of Squares (RSS) was 41.51, measuring the error of prediction. Demand, by the sales index ($q_t$), is estimated by Equation 3, where quality and the previous period's price have positive and significant impacts on demand, and the relationship between time and demand is nonlinear. The designed models reflect the complex interactions among pricing, quality, and demand. The quality index is negatively correlated with discounts, i.e., more quality reduces the need for discounts. The discount function shows how price, quality, and stock levels determine pricing measures to provide d iminishing discounts for increasing prices and quality, and unsold stocks to provide greater discounts to induce sales more quickly. The demand function shows how prices, quality, and time operate together to determine overall sales performance, where demand increases with time but at a declining rate, and higher prices lower current demand. These findings reflect the importance of quality, price, and stock balancing to achieve maximum profitability and sales.

#### Price Discounts and Profit

It was observed that the price discounts every 3–4 hours earned the highest profit.

Discounts provided at higher intervals (e.g., every 1–2 hours) resulted in rapid price reductions and minimal overall profit since buyers considered the product to be of lesser quality. In the Hourly discount, the price decreases to 95.26 in the second hour and to 60.65 in the third hour. This steep drop represents a rapid loss of product value over short periods (Chart 3).

Average discount stands at 14.83%, and the average discount rate stands at 14.83% per hour. As compared to this, using a discount every two hours demonstrates a lower price reduction. Here, the price goes down to 89.28 in the first period and reaches 61.78 in the third period. The average discount is 20.76%, and the average discount rate is 10.38% per hour. This shows that longer time intervals can reduce the loss of the value. However, discounts taken at longer intervals (e.g., every 5 to 12 hours) yielded fewer sales and more waste, since product quality deteriorates greatly before selling. A discount taken every three hours significantly moderates the price drop. Here, the price drops to 82.39 in the first interval and becomes 44.42% in the third interval. The average discount rate is 31.85% and 10.62% an hour. This indicates that longer periods can handle the loss of value more effectively. Each four-hour discount shows a declining trend. In this, the price drops to 75.80 in the first interval and to 37.15% in the third interval. The mean rate of discount is 37.59% and 9.40% an hour. This clearly shows that larger time intervals can handle the decline in value better. Finally, a discount every five hours shows the highest stability in prices. Here, the price drops to 70.70 for the first interval and to 38.01 for the third interval. The average discount rate is 53.52% and 10.70% hourly. This supported that the longer time intervals worked more efficiently. For discounts every six hours or less frequently, the lowering of the price is much more gradual, and prices are maintained more stable for longer intervals. The research also determined that dynamic pricing methods, which change prices in response to real-time information, outperform static pricing when it comes to profit maximization and waste reduction (Chart 4). The trend for profit uniformly rises in the discount intervals of 1 to 4 hours. For instance, profit increases from 32.70 in hourly discount to 70.84 in 4-hour discount.

This is due to greater customer involvement during these intervals. The growth rate of profit was positive during such time intervals. That is, the difference in profit rate is 5.22 units between the hour and 2-hour discount, 5.70 units between 2-hour and 3-hour discount, and 3.46 units between the 3-hour and 4-hour discount. This indicates that standard short-term discounts can enhance demand and maximize profits.

Profits begin declining after a 4-hour interval. For instance, the profit drops from 70.84 in the discount of 4 hours to 70.76 in the discount of 5 hours. The decline is tremendous: from 4-hour to 5-hour discounts, the profit drops by eight units; from 5-hour to 6-hour discounts, the profit drops by 12.3 units; from 6-hour to 7-hour discounts, the profit drops by 8.82 units; and from 7-hour to 8-hour discounts, the profit drops by 17.8 units. The steepest decline is between 5-hour and 6-hour intervals, indicating that the profit decline accelerates after 5 hours. Between 9 and 12-hour intervals, the rate of profit loss accelerates drastically. This indicates a reduction in demand or the reduced utility of discounts within these hours. This sharp profit decline may be accounted for by the degradation of product quality or declining customer desire for protracted discount provisions. Every discount, every 1 to 4 hours, provides maximum profit and is strongest in that it induces faster sales and maximum profitability. But after the 4-hour mark, profit dips, and it takes strategic considerations such as combining 3-hour and 5-hour discounts to balance losses. In 5- to 8-hour intervals, in which profit loss is large but relatively slower, methods such as raising offer attractiveness or providing additional services (e.g., free packaging) can be applied. In 9-to-12-hour intervals, where profit loss is severe, long-term discounts should be avoided, and other approaches such as bundle sales or companion product promotion are best. Profit reduction steepens to become negative after the 4-hour interval, with precipitous falls at 4-hour and 5-hour discounts (-8 units), 5-hour and 6-hour discounts (-12.3 units), 6-hour and 7-hour discounts (-8.82 units), and 7-hour and 8-hour discounts (-17.8 units). These findings underscore the necessity for adaptively varying discounting practices as a function of customer reaction and product characteristics to achieve optimal profitability.

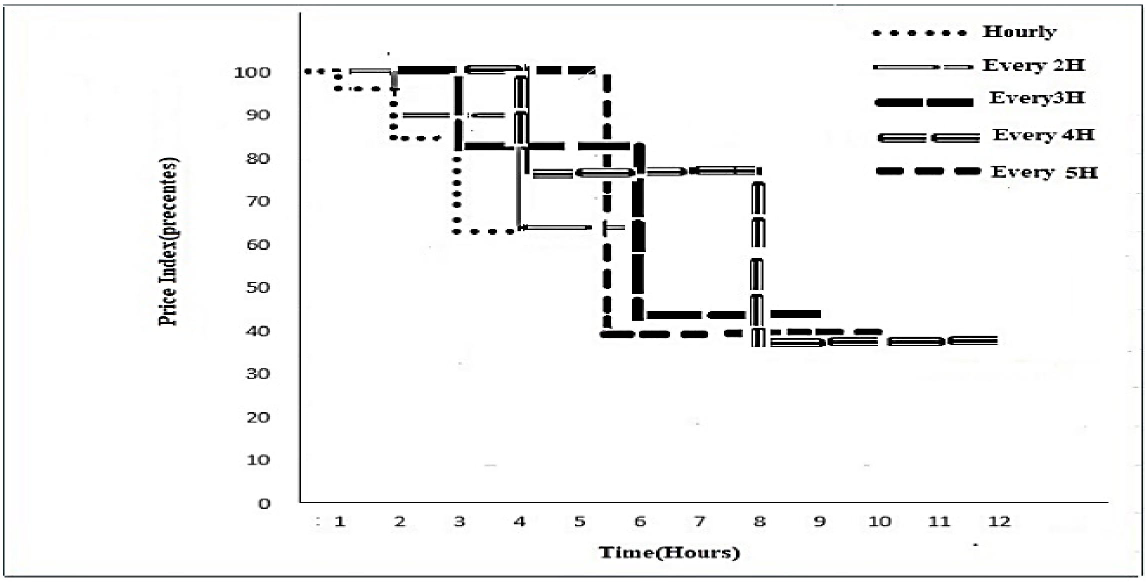


**Chart 3- Price discounts over different periods (research findings)**

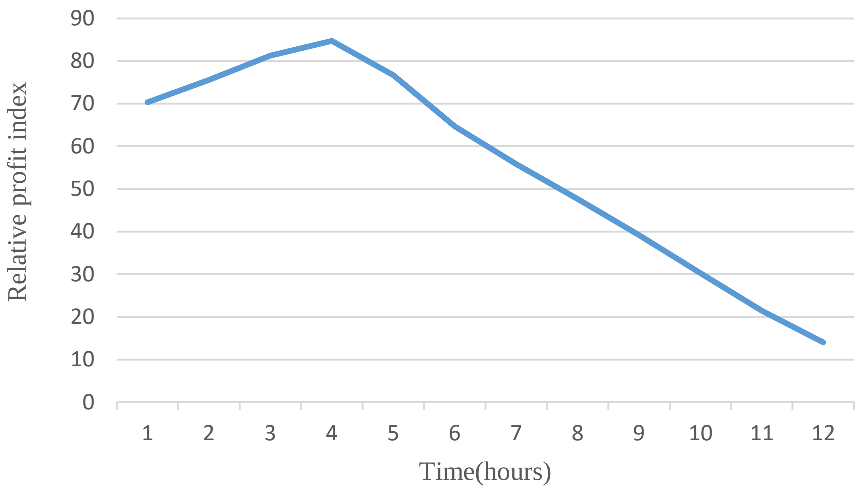


**Chart 4- Profit trends in different discount periods**
(Research findings)

The difference in profit depends on two factors: price reduction, which increases demand and sales; and quality reduction, which reduces demand and sales. As long as price reduction is more attractive to consumers than quality reduction is, the sales increase. But after the 4-hour interval, the negative impact of quality depreciation takes control over the attractiveness of price cutbacks, resulting in a decline in sales. Overall, 1- to 4-

hour discounts are better and achieve the maximum profit, while discounts over 10 hours lead to a great loss of profit. Thus, after a 4-hour gap, 3-hour and 5-hour discounts become better alternatives to increase sales and stay profitable, and long-term discounts need to be used cautiously and methodically.

## Discussion

### Optimal Discount Intervals

The findings of this study determine optimal discount times as a measure of profit maximization and wastage reduction of perishable goods such as tomatoes. The findings suggest that price discounts to be implemented within 3–4 hours to achieve the best outcomes.

This is a compromise between stimulating the demand from the consumers and maintaining the quality of the goods. Discounts with a smaller time gap between them (e.g., every 1–2 h) may lead to frequent price reduction, which can strip the profit and create an impression of low quality of the product. Discounts with larger intervals (e.g., every 5–7 h) can create more wastage, as the product quality is wasted heavily before sale. By applying discounts at 3 to 4-hour intervals, retailers can control their inventory turnovers while maintaining the perceived value of their offerings. Such a discovery is in line with prior studies involving dynamic pricing strategies that stress making adjustments in real time depending on the levels of quality deterioration, availability, and demand (Elmaghraby & Keskinocak, 2003).

For instance, Liu *et al.* (2023) demonstrated that data-driven dynamic pricing frameworks for omni-channel retailing can significantly reduce waste and increase profitability, especially in situations of unpredictable demands. Similarly, Elmaghraby & Keskinocak (2003) observed that early discounts would increase profit and reduce waste. Similarly, Kayikci *et al.* (2023) proposed a data-driven pricing framework that significantly reduced food waste and increased retail profitability. These studies altogether attest to the significance of evidence-based decision-making for maximizing pricing strategies for perishables, as illustrated in the current study, which reveals that short discount periods (1 to 4 hours) significantly maximize profitability while effectively controlling quality degradation and inventory levels.

### Maintaining Quality Degradation

Quality degradation is a significant dilemma for retailers handling perishable products. The study found that tomatoes had a very severe quality loss within 24 hours, losing their quality index from 0.66 at the beginning of the day to 0.14 in the evening. This rapid spoilage is an indicator of the need for effective storage and stock management. For example, Sun *et al.* (2023) emphasized temperature and humidity management for the sake of maintaining product quality, which supports findings in the present study. Similarly, Kayikci *et al.* (2022) established that the inclusion of real-time environmental factors, such as temperature and humidity, into dynamic pricing equations can optimize sales while reducing wastage. To minimize degradation of quality, the retailers are urged to try and improve storage conditions, for example, keeping the products cool and dry.

Cold, dry storage of tomatoes can slow the process of degradation and extend their shelf life, as indicated by Sun *et al.* (2023). Additionally, retailers are urged to utilize "last chance" promotions to dispose of products nearing the end of their shelf life. These offers pressure buyers into buying the product before it spoils. It is as per the recommendation of Elmaghraby *et al.* (2003), who mention the application of dynamic discounts in reducing wastage and increasing profit. The study also highlights the applicability of including quality parameters in price models.

Through real-time tracking of quality decline, retailers can make evidence-based decisions regarding price adjustments and inventory management. This not only reduces wastage but also optimizes customer satisfaction as consumers receive the highest-quality products. Scholz & Kulko (2022) demonstrated that employing dynamic pricing models that depend on freshness would reduce food wastage by as much as 53.6% while optimizing retailer revenue by up to 10%. Liu *et al.* (2023) used reinforcement learning algorithms to improve the accuracy of prices by 35% and reduce waste, providing evidence for the advantage of real-time quality monitoring in the optimization of prices. All these findings together demonstrate the importance of data-driven decision-making in addressing perishable products. This research, despite providing valuable information on the dynamic pricing of perishable products, has some drawbacks. First, information was taken from only three stores within a single city, and consequently, the findings might be non-representative. Second, the model is based on homogeneous seller conduct and does not consider real external drivers such as weather, promotions, or rival prices. Third, actual-time quality was calculated based on estimated functions rather than direct technology or sensor readings. Future research can expand the geographic scope and utilize better quality monitoring tools or stronger market forces

#### Consumer Perception

This study highlights the critical role of consumer perception in dynamic pricing strategies. While discounts may increase demand, over-discounting may prompt consumers to doubt product quality and reduce brand trust and long-term loyalty. Zheng *et al.* (2022) illustrated that price-reduction discounts increase perceived quality uncertainty and therefore may have a detrimental effect on consumer purchase intentions. To be able to effectively balance price competition and brand image protection, stores have the option to use slow price cuts rather than drastic and deep price reductions. Drastic and sudden price cuts risk causing customers to question the freshness and quality of products, which can undermine brand trust and loyalty in the long term. Slow cuts allow customers to enjoy sustained value while still getting better prices in the long term. Aschemann-Witzel *et al.* (2015) point out that food purchasing is influenced by consumer attitudes and that deep discounting can send a hidden message of suboptimal quality, leading to more food waste as consumers avoid bargains.

Hence, an effective price strategy with price updates being aligned with product freshness can help in the reduction of waste and consumer trust protection. This practice not only promotes sustainable consumption behavior but also enhances the profitability overall through trust establishment and repeat purchases. The value of the goods must also be communicated to customers by retailers. For example, projecting the freshness and quality of tomatoes through the installation of signs within the stores or executing digital promotions can instill that the good is value for the price even after discounting. This is in concordance with the appeal of Syed *et al.* (2024) that transparency and communication are key in maintaining consumer satisfaction and trust. By having trusting and transparent relationships with consumers, retailers can enhance their brand reputation and provide long-term profitability, as shown in previous studies by data-driven and consumer-driven pricing approaches.

### Conclusion

This study demonstrates the importance of dynamic pricing methods to manage perishable commodities such as tomatoes. Through the imposition of price discounts at optimal time intervals, retailers can maximize profit, avoid wastage, and maintain product quality. From these findings, it is suggested that discounts must be applied every 3–4 hours for optimal results. This approach strikes a balance between stimulating demand and protecting product value, enabling retailers to manage their inventories effectively while meeting consumers. Proper storage and inventory handling practices also need to be emphasized to minimize quality loss, according to this study. By maintaining temperature and humidity levels and employing "last chance" promotions, retailers can extend the shelf life of their products and reduce waste. Furthermore, this study sheds light on the importance of consumers' price strategy perception. Brand image and price attractiveness must be well balanced by retailers in a way that will capture customers' trust and loyalty. Future research should also examine whether these strategies are effective in other perishable products, such as dairy, meat, and bakery, and in alternative market environments. In addition, future studies can investigate the effects of emerging technologies such as artificial intelligence and blockchain on maximizing the dynamic pricing and inventories of perishable goods. The problems of dealing with perishable products can be addressed and sustainable business encouraged by improving and innovating even more for retailers. The results of the present research are as follows:

1. Discounting prices at optimal time periods (every 3–4 hours) maximizes profit with the least amount of waste.
2. It is a perfect trade-off between stimulating demand and product value.
3. Consumers' perception and expectations play vital roles in pricing strategies, and retailers must strike a balance between price appeal and product quality.

These findings show that dynamic pricing and smart inventory control can help retailers make efficient use of perishable products.

Suggestions for future research incorporating other factors affecting quality, i.e., temperature, humidity, and variety.

• Exploring the impact of consumers' price expectations on the demand function.

• Enlarging the study to other perishables such as dairy, meat.

• Exploring the use of new technology in optimizing dynamic pricing and inventory management, e.g., artificial.

**Acknowledgments**

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## Appendix

**Heteroskedasticity Test: Breusch-Pagan-Godfrey Null hypothesis: Homoskedasticity**

| **Model** Statistics | **Price Change** Stat. (p-Value) | **Demand** |
|---|---|---|
| F-statistic | 2.13(0.097) | 2.348(0.053) |
| Obs*R-squared | 6.3248(0.097) | 9.287(0.054) |
| Scaled explained SS | 3.468(0.3249) | 11.719(0.02) |

**Test to detect collinearity**

| **D.V: Price Change** | **Centered VIF** | **D.V: Demand** | **Centered VIF** |
|---|---|---|---|
| PRICE | 1.200543 | (PRICE_INDEX)^-1 | 1.756014 |
| QUALITY | 1.181043 | QUALITY_INDEX^5 | 1.793120 |
| REMAIN | 1.040684 | PERIOD^2 | 1.080800 |

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# ارائه الگویی برای استرتژی تخفیف قیمت در محصولات فاسدشدنی: مطالعه موردی گوجه‌فرنگی تازه

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## چکیده

بسیاری از محصولات کشاورزی تازه، مانند میوه‌ها و سبزیجات، به‌شدت فسادپذیر هستند و حفظ کیفیت آن‌ها از طریق نگهداری در شرایط سردخانه‌ای یا شرایط بهینه، می‌تواند برای خرده‌فروشان و تولیدکنندگان کوچک از نظر اقتصادی چالش‌برانگیز باشد. گاهی این محصولات در کمتر از ۲۴ ساعت کیفیت و بازار پسندی خود را از دست می دهند. لازم است خرده‌فروش با استفاده از استراتژی تخفیف قیمت متناسب با کاهش کیفیت از هدر رفتن سرمایه خود جلوگیری کند. چالش اصلی در اتخاذ این استراتژی، تعیین زمان و میزان تخفیف قیمت است. برای بهینه‌سازی تنزیل قیمت، چهار تابع باید برآورد شود: الف) تابع کیفیت وابسته به زمان، ب) تابع تغییر قیمت، ج) تابع تقاضا که تابعی از قیمت و کیفیت است، و د) تابع هدف که در اینجا به‌عنوان تابع سود خرده‌فروش در نظر گرفته می‌شود. ما از مدل‌های قیمت‌گذاری پویا استفاده می‌کنیم که عواملی مانند کاهش کیفیت، سطح موجودی، و رفتار مصرف‌کننده را ادغام می‌کند. برای ارائه بینش واقعی، داده‌های تحقیق از سه فروشگاه میوه و تره‌بار در شهر گرگان جمع‌آوری شد. مدت زمان سه ماه و شامل تمام روزهای کاری بود. از هر فروشنده خواسته شد تا قیمت و مقدار فروش را به‌صورت ساعتی از ابتدا تا پایان روز کاری گزارش دهد. به این ترتیب از هر فروشگاه حدود ۱۰۰۰ داده ثبت شد. گوجه‌فرنگی به‌دلیل مصرف گسترده، عرضه مداوم و فسادپذیری سریع به‌عنوان مطالعه موردی انتخاب شد. نتایج نشان می‌دهد که تخفیف‌های قیمت می‌تواند به‌طور قابل‌توجهی سودآوری را افزایش دهد و در عین حال خطر محصولات فروخته نشده و فاسد را کاهش دهد. به‌طور خاص، یافته‌ها نشان می‌دهد که اجرای تخفیف‌های قیمتی هر ۳ تا ۴ ساعت، بیشترین سودآوری را به همراه داشته است. میانگین تخفیف ۳۵ درصد است که منجر به افزایش ۸۲ درصدی سود ناخالص می‌شود. در مقابل، فواصل تخفیف کوتاه‌تر (هر ۱ تا ۲ ساعت) با میانگین تخفیف ۱۸ درصد، سود ناخالص را تا ۷۳ درصد بهبود بخشید. از سوی دیگر، فواصل تخفیف‌های طولانی‌تر (هر پنج تا هفت ساعت) با میانگین تخفیف ۴۶ درصد منجر به افزایش ۶۶ درصدی سود ناخالص شد. علاوه بر این، این مطالعه بر اهمیت درک مصرف‌کننده در موفقیت استراتژی‌های قیمت‌گذاری پویا تأکید می‌کند. تخفیف بیش از حد می‌تواند منجر به درک کیفیت پایین محصول شود که ممکن است بر اعتماد مصرف‌کننده و اعتبار طولانی مدت فروشگاه تأثیر منفی بگذارد. پژوهش‌های آینده می‌توانند با افزودن متغیرهای مؤثر بر کیفیت محصول- مانند دما، رطوبت و نوع محصول- چارچوب فعلی را توسعه دهند. همچنین، تحلیل نقش انتظارات قیمتی مصرف‌کنندگان در شکل‌گیری تابع تقاضا، تعمیم مدل به سایر محصولات فسادپذیر از جمله لبنیات و گوشت، و استفاده از فناوری‌های نوین نظیر هوش مصنوعی و بلاک‌چین در بهینه‌سازی قیمت‌گذاری پویا و مدیریت موجودی، می‌تواند در ارتقای اثربخشی راهبردهای فروش محصولات فسادپذیر نقش مهمی ایفا کند.

**واژه‌های کلیدی**: استراتژی قیمت‌گذاری پویا، بازارهای خرده‌فروشی، تخفیف‌های قیمتی، کاهش کیفیت، گوجه‌فرنگی

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