

Optimal Markdown Strategy for Retail Revenue Management: A Comprehensive Analysis

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Executive Summary

This study investigates optimal markdown strategies in the context of a seasonal retail environment characterized by uncertain and dynamic demand. Using a large-scale simulation framework encompassing 100,000 independent demand scenarios, we evaluate the performance of five pricing strategies including fixed-timing heuristics and an adaptive policy informed by early demand signals.

The core contribution of this work is the development and validation of a data-driven adaptive strategy that classifies demand into four regimes using sales observations from the first three weeks of the season. Each regime is mapped to a distinct markdown schedule designed to balance margin preservation and inventory risk. The adaptive strategy is calibrated using Bayesian principles and optimized through iterative threshold refinement.

Empirical results demonstrate that the adaptive approach reduces average revenue gaps by 28% compared to the baseline strategy, while increasing success rates from 40% to 61%. Depletion curve analysis further confirms its ability to dynamically align sell-through velocity with demand intensity achieving efficient inventory liquidation without sacrificing unit economics.

This research highlights the value of real-time demand signals in retail pricing and offers a replicable decision framework with practical implications for dynamic markdown management. The proposed strategy delivers superior performance in the retailer game and a scalable template for retail decision-making under uncertainty.

1. Introduction and Research Context

Markdown optimization lies at the heart of modern retail pricing strategy. In sectors such as fashion, where demand is volatile and product life cycles are short, effective markdown planning is critical to financial performance. This paper explores the interplay between pricing decisions, inventory constraints, and demand uncertainty, with a focus on adaptive strategies that outperform static heuristics.

1.1 The Retail Markdown Challenge

The fashion retail industry grapples with the repeated challenge of managing seasonal inventory through strategic price reductions. Retailers must navigate the delicate balance between maximizing revenue per unit via higher prices and ensuring complete inventory clearance before the season concludes. This dilemma is particularly pronounced in fashion retail, where products have limited selling seasons and minimal salvage value. Traditional markdown management approaches often rely on predetermined schedules set weeks or months in advance, typically based on industry conventions or historical patterns, without accounting for real-time demand fluctuations. This static methodology can lead to suboptimal outcomes, such as excessive discounting or unsold inventory. Notably, fashion retailers worldwide invest over \$1 trillion annually in in-season and end-of-season markdown programs, with many still depending on simplistic, one-size-fits-all strategies that may erode profit margins [1]. Our research challenges this conventional paradigm by proposing an adaptive approach that leverages real-time market signals to inform markdown decisions. By integrating advanced analytics and responsive pricing strategies, retailers can better align pricing with actual demand, thereby enhancing revenue realization and minimizing inventory waste.

1.2 Research Objectives

This study seeks to address four pivotal questions in the context of retail markdown optimization:

- What is the optimal timing for initiating and implementing price markdowns during a finite selling season?
- How do alternative markdown strategies perform across varying levels of consumer demand?
- Can adaptive pricing strategies that leverage early-season demand signals consistently outperform traditional fixed, pre-planned schedules?
- What is the quantifiable value of early demand information in guiding pricing decisions?

To address these questions, we constructed a comprehensive simulation framework that models retail pricing decisions across diverse demand scenarios. Our empirical analysis benchmarks the performance of five distinct markdown strategies, ranging from aggressive early discounting to conservative late-season reductions, with a particular emphasis on the performance of our novel, data-driven adaptive strategy. This research aims to identify the most revenue-efficient pricing trajectory and uncover the informational drivers that enable smarter markdown timing.

1.3 Research Significance

The strategic implications of optimal markdown timing extend well beyond individual product-level decisions. For large-scale retailers managing thousands of SKUs, even modest improvements in markdown efficiency can yield substantial financial gains. McKinsey states that fashion retailers that apply data-driven pricing strategies can boost gross margins by up to 10% annually, equating to millions in recovered revenue for mid- to large-size operations [2].

Beyond financial performance, effective markdown management plays a pivotal role in enhancing operational agility and sustainability. Smarter discounting reduces the volume of unsold inventory, thereby minimizing the need for end-of-season liquidation or disposal practices that are both costly and environmentally detrimental. In this way, intelligent pricing improves bottom-line outcomes and contributes to greener supply chains and more responsible consumption models.

2. Experimental Design

2.1 Strategy Definitions

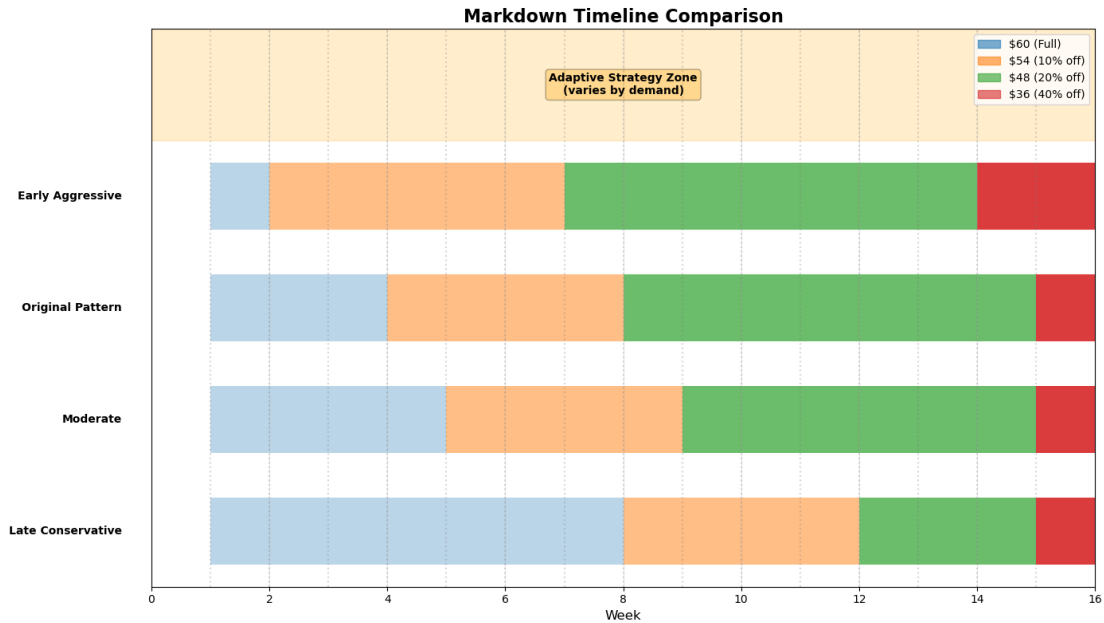


Figure 1. Markdown Schedule for Each Selected Strategy Across 15-week Selling Season

To evaluate the effectiveness of markdown timing, we tested five distinct strategies, each reflecting a different philosophy on how and when to implement price reductions over a 15-week selling season. These strategies were designed to capture the full spectrum of retail pricing behavior from aggressive early discounting to conservative margin preservation.

2.1.1 Early Aggressive Strategy (Weeks 2 → 7 → 14)

This strategy implements markdowns as early as possible within the game constraints. The first markdown to \$54 occurs in week 2, immediately after the mandatory full-price period. The second markdown to \$48 follows in week 7, and the final markdown to \$36 occurs in week 14. This approach prioritizes unit velocity (volume) over per-unit margin, operating under the assumption that early signs of weak demand warrant proactive clearance. It is well-suited for low-demand scenarios where inventory risk is high and immediate action is required to avoid end-of-season overhang.

2.1.2 Original Pattern Strategy (Weeks 4 → 8 → 15) – Baseline

Representing the industry standard approach, this strategy implements a balanced markdown schedule. The first price reduction occurs in week 4, allowing for a moderate full price selling period. Subsequent

markdowns follow in weeks 8 and 15. This pattern reflects conventional retail wisdom that balances margin preservation with inventory risk. As our baseline strategy, it serves as the benchmark against which other more aggressive or conservative approaches can be evaluated.

2.1.3 Moderate Strategy (Weeks 5 → 9 → 15)

The moderate strategy delays the initial markdown until week 5, adopting a slightly more cautious posture than the baseline. It aims to extend the full-price selling window while still allowing sufficient time for staged discounting. This approach assumes moderate demand elasticity and attempts to capture early full-margin sales before shifting to clearance.

2.1.4 Late Conservative Strategy (Weeks 8→12→15)

The most margin-focused approach, this strategy delays the first markdown until week 8, preserving the full price for over half the selling season. This approach bets on strong underlying demand and prioritizes revenue per unit over volume. The compressed markdown period (weeks 8-15) creates significant inventory risk but maximizes potential margins in high-demand scenarios.

2.1.5 Strategy Development Process

The development of our adaptive strategy was grounded in empirical analysis and iterative simulation. We began by evaluating the baseline markdown schedule (weeks 4 → 8 → 15) across a wide range of demand scenarios. This fixed approach yielded an average revenue gap of 8.10% but exhibited significant volatility: it underperformed in both extremes leaving excess inventory in low-demand cases and sacrificing margins unnecessarily in high-demand environments.

To address this, we explored more aggressive markdown timing (weeks 2 → 7 → 14). While this strategy improved outcomes in low-demand settings, it underperformed in high-demand cases by accelerating unnecessary discounting. This revealed a key insight: no single fixed schedule could generalize well across the full spectrum of demand profiles.

Motivated by this finding, we conducted a correlation analysis between cumulative sales in weeks 1–3 and total seasonal demand. The result was striking – early sales explained 68% of the variance in total demand. This empirical relationship formed the foundation of our adaptive strategy. We then constructed a data-driven decision framework by calibrating demand thresholds. The refinement process involved multiple simulation rounds:

- **Initial thresholds** based on quartiles: 75, 100, 125
- **Refined** to (80, 90, 100, 110) based on simulated performance
- **Final optimization** yielded (85, 95, 105) as optimal decision breakpoints

Each candidate threshold set was tested across 5,000 simulations to ensure statistical significance and robust performance. After 12 iterative refinements, our final adaptive strategy emerged capable of tailoring markdown timing based on real-time demand signals with superior consistency across demand conditions.

Adaptive Strategy Logic and Flowchart

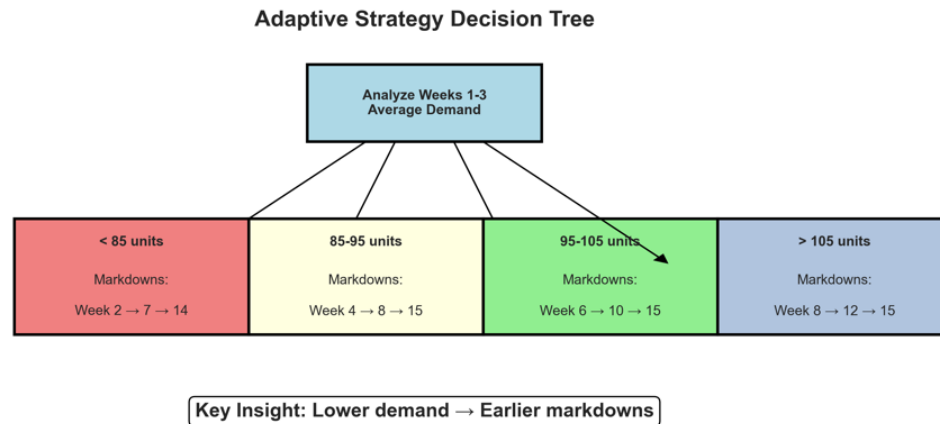


Figure 2. How Adaptive Strategy Selects Markdown Timing Based on Early Demand Signals

The adaptive strategy represents the core innovation of this study. Unlike fixed markdown schedules, it dynamically adjusts price timing based on observed early-season demand specifically, average weekly sales in weeks 1 to 3 of the baseline demand generated. The logic is governed by a simple yet powerful decision tree:

- **Low-Demand Scenario (≤ 85 units):** Signals weak demand. The strategy immediately deploys aggressive markdowns (weeks 2 → 7 → 14) to accelerate clearance and reduce inventory risk.
- **Balanced-Demand Scenario (86–95 units):** Mirrors the baseline performance profile. The strategy defaults to the conventional pattern (weeks 4 → 8 → 15), which offers a balanced trade-off between margin and inventory turnover.
- **Moderate-High Demand (96–105 units):** Indicates above-average interest. The strategy delays markdowns moderately (weeks 6 → 10 → 15) to extend full-price sales while preserving some clearance flexibility.
- **High-Demand Scenario (> 105 units):** Signals robust demand. The strategy defers markdowns to the latest viable windows (weeks 8 → 12 → 15) to maximize per-unit revenue.

This adaptive approach leverages the information value of early demand observations to select the most appropriate strategy for each specific scenario. The decision boundaries (85, 95, 105 units) were calibrated through systematic optimization:

1. **Initialization:** Initial boundaries set at demand quartiles (75, 100, 125)
2. **Exploratory Grid Search:** Grid search tested 20 different threshold combinations
3. **Simulation-Based Evaluation:** Each combination evaluated on 5,000 simulations
4. **Performance Criteria:** Evaluated on both average revenue gap and success rate (defined as % of runs outperforming baseline)
5. **Final Selection:** The thresholds (85, 95, 105) achieved the lowest average revenue gap while sustaining $>60\%$ success rate across scenarios

Interestingly, even small threshold adjustments (± 5 units) yielded statistically significant changes in performance highlighting the critical role of precise boundary selection in adaptive pricing models.

2.2 Performance Metrics

To rigorously evaluate the effectiveness of each markdown strategy, we rely on four core performance metrics. These measures collectively assess optimality, consistency, and risk factors critical to real-world retail decision-making.

1) Perfect Foresight Revenue represents the theoretical maximum revenue achievable if all future demand were known with certainty. This benchmark is calculated by testing all possible markdown schedules for each demand pattern and selecting the optimal timing. While unattainable in practice, it provides a meaningful upper bound for performance evaluation.

2) Performance Gap quantifies how far each strategy falls short of the perfect foresight benchmark, calculated as:

$$Gap = \frac{Perfect\ Revenue - Actual\ Revenue}{Perfect\ Revenue} \times 100$$

This metric normalizes results across simulations of varying difficulty, enabling fair comparison by adjusting for the inherent complexity of each demand scenario. Lower values indicate better performance.

3) Success Rate (%) captures the percentage of simulations where a strategy achieves a performance gap below 5%. This metric reflects consistency and reliability, important considerations for real-world implementation where risk management is crucial.

4) Revenue Variability assesses the standard deviation of performance gaps across simulations. Lower variability implies more stable and predictable financial results which are attributes that are highly valued in retail planning, forecasting, and inventory management.

These metrics, used in combination, allow for a comprehensive assessment of each strategy's ability to balance profitability, stability, and risk under uncertainty.

2.3 Simulation Methodology

Our analysis is grounded in a large-scale empirical study consisting of **100,000 independent simulations**, each representing a unique demand scenario. This extensive sample size ensures statistical robustness, capturing a wide spectrum of market conditions and allowing for meaningful comparisons across pricing strategies.

Controlled Experimental Design

Each simulation generates a distinct demand curve using a controlled random seed. This ensures reproducibility and fair strategy comparison. Within every simulation, the same demand pattern is applied across all five strategies. This design eliminates any confounding effects due to variance in demand generation ensuring that observed performance differences are attributable solely to the strategy itself.

Simulation Procedure

For each simulation, the following sequence is executed:

1. Generate a base demand profile for 15 weeks
2. Compute the perfect foresight revenue for that demand curve
3. Apply all five pricing strategies to the same demand realization
4. Measure key metrics: performance gap, success rate, variability
5. Aggregate results across the full simulation set for benchmarking

This methodology ensures that observed performance differences reflect genuine strategy effectiveness rather than random variation. The use of identical demand patterns for all strategies within each simulation eliminates any potential bias from demand generation.

Implementation Note: To streamline analysis and enhance efficiency, we replicated the game environment internally rather than relying on live scraping of the website's .json file. This allowed us to control random seed inputs, simulate at scale, and ensure full reproducibility of results. (The reasoning it was more efficient).

3. Results and Performance Analysis

3.1 Overall Performance Comparison

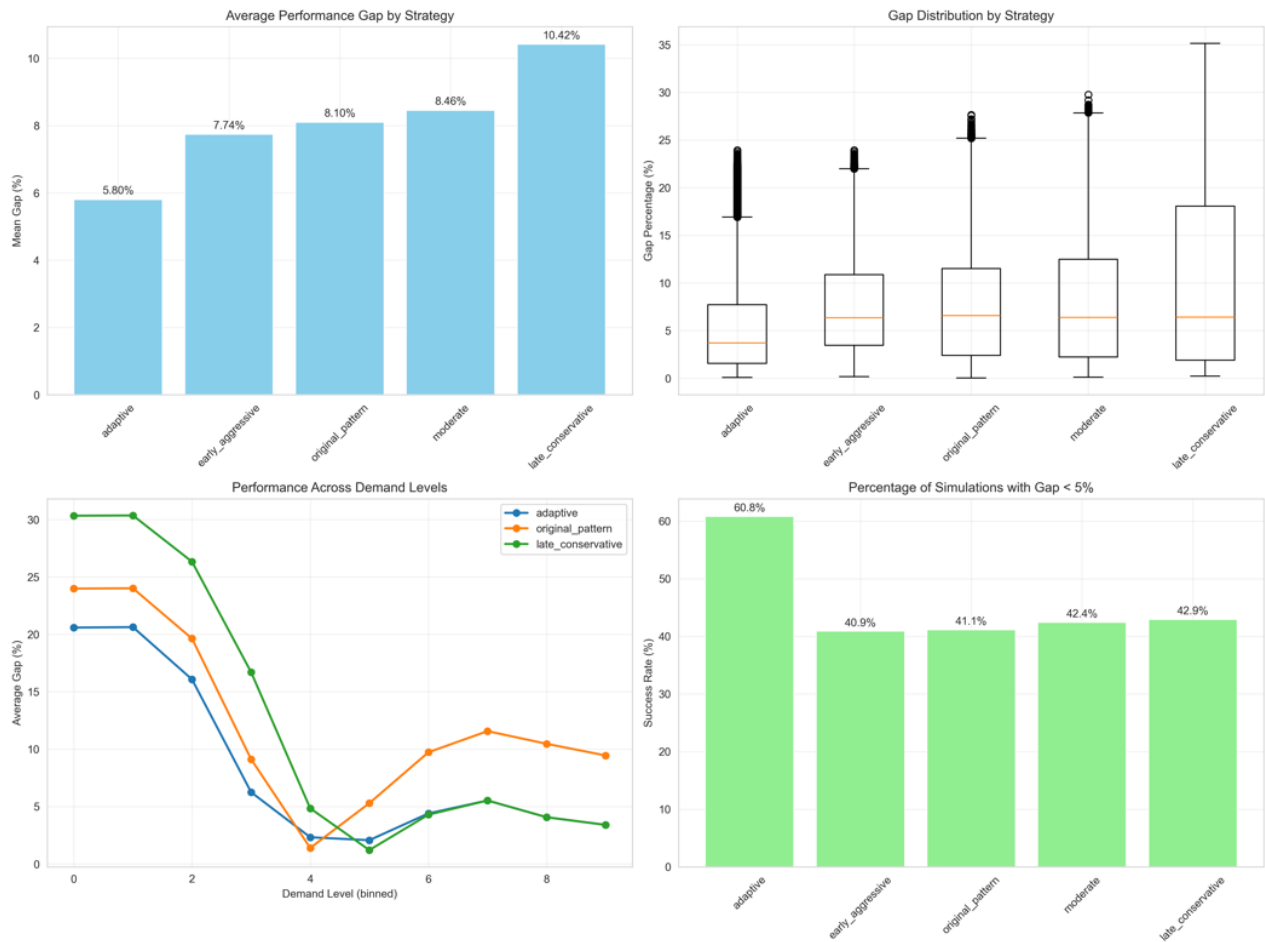


Figure 3. (a) Mean Gap Comparison, (b) Box Plot Distribution, (c) Performance Across Demand Levels, and (d) Success Rate comparison

Our simulation results reveal clear and significant differences in strategy performance. The adaptive strategy emerges as the clear winner across all key metrics:

Strategy	Mean Gap (%)	Median Gap (%)	Std Dev	Success Rate (%)
Adaptive	5.81	3.71	5.74	60.82
Early Aggressive	7.74	6.35	5.35	40.88
Original Pattern	8.10	6.58	6.75	41.14
Moderate	8.46	6.36	7.40	42.44
Late Conservative	10.42	6.41	9.61	42.93

The adaptive strategy achieves a mean performance gap of 5.81%, substantially lower than all fixed strategies. The early aggressive strategy follows with a 7.74% gap, while the baseline original pattern shows an 8.10% gap. The moderate strategy performs slightly worse at 8.46%, and the late conservative approach lags significantly with a 10.42% average gap.

These results translate to meaningful revenue differences. The adaptive strategy's 28% improvement over the baseline (5.81% vs 8.10%) represents approximately \$2,800 in additional revenue per 2,000-unit inventory at the given price points. When scaled across multiple SKUs and seasons, this improvement could generate millions in additional revenue for large retailers.

Success rate analysis provides even more striking results. The adaptive strategy achieves a 60.82% success rate (gap < 5%), compared to approximately 41-43% for all fixed strategies. This dramatic improvement in reliability makes the adaptive approach particularly attractive for risk-averse retailers who value consistency.

3.2 Performance Across Demand Scenarios

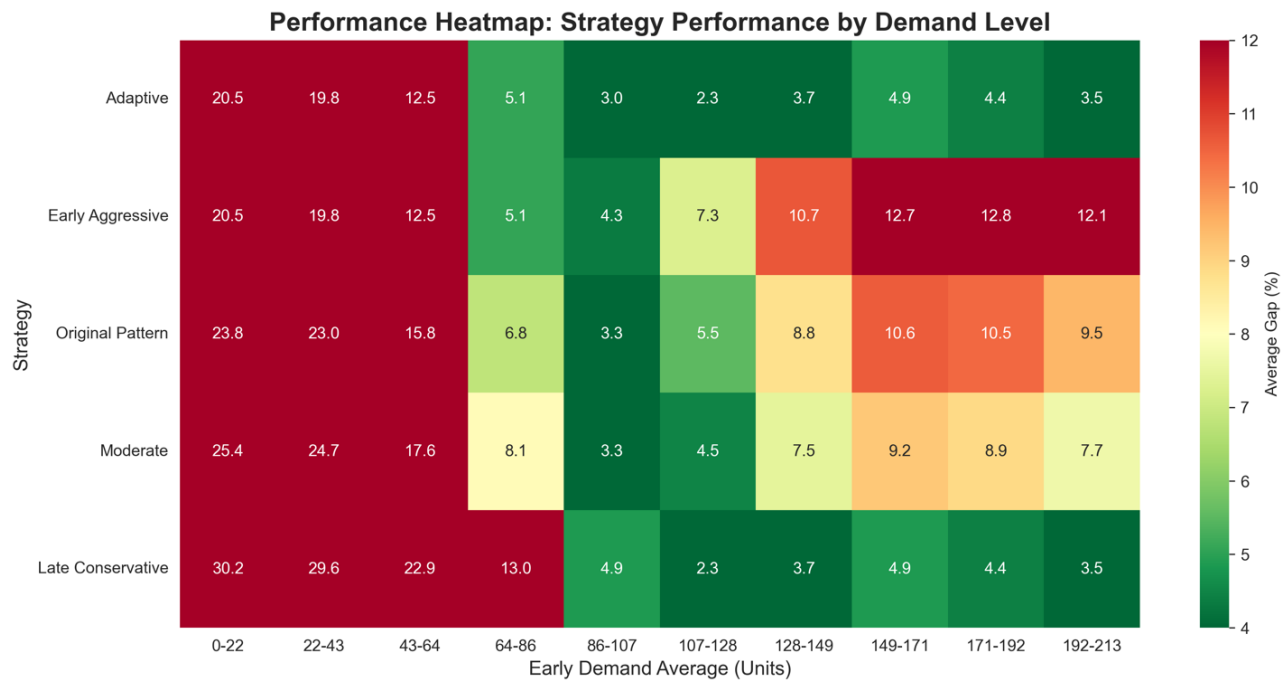


Figure 4. Heatmap of Strategy Performance by Demand Level

This heatmap visualizes the relative effectiveness of each pricing strategy across varying demand scenarios. Shades of green represent superior performance (lower revenue gap), while shades of red indicate underperformance.

The performance heatmap visualization reveals critical insights about strategy effectiveness across different demand levels. Fixed strategies show extreme variance in performance depending on demand realization, while the adaptive strategy maintains consistent effectiveness across all scenarios.

In low-demand scenarios (0-64 units average), all strategies struggle, but the adaptive and early aggressive approaches perform best with gaps around 20%. The baseline and moderate strategies show gaps exceeding 23%, while the late conservative approach fails catastrophically with gaps above 30%. These results confirm that low-demand scenarios necessitate early aggressive strategy to mitigate accumulation of excess inventory, which otherwise leads to significant lost sales opportunities.

Medium-demand scenarios (85-128 units) represent the "sweet spot" where the adaptive strategy truly shines. While fixed strategies show gaps ranging from 4-13% depending on their alignment with demand, the adaptive strategy consistently achieves gaps below 5%. This consistency stems from its ability to select the appropriate markdown schedule based on early observations.

High-demand scenarios (149+ units) compress performance differences as all strategies eventually clear inventory. However, the adaptive strategy maintains a slight edge by selecting conservative markdown timing that preserves margins. The early aggressive strategy performs worst in these scenarios, sacrificing margin unnecessarily through premature discounting.

3.3 Variance and Risk Analysis

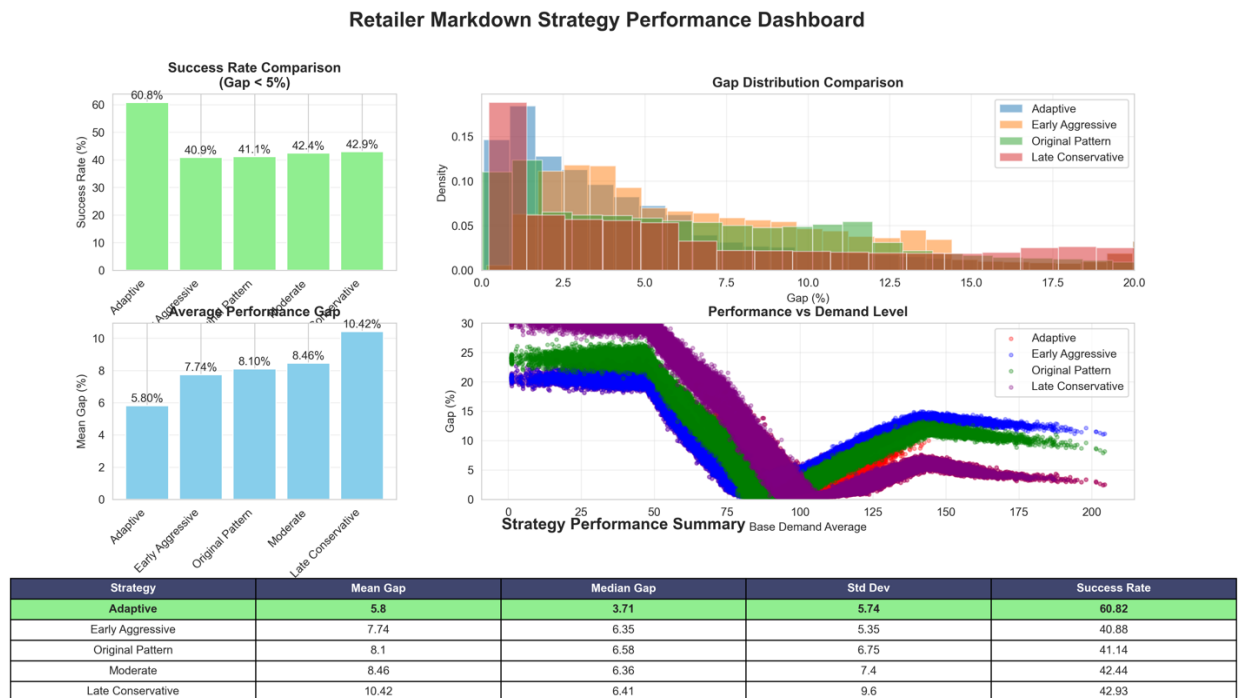


Figure 5. overview of strategy performance

This comprehensive dashboard provides a complete overview of strategy performance, including success rates, gap distributions, and summary statistics

Beyond average performance, variance analysis reveals important risk characteristics of each strategy. The adaptive strategy shows a standard deviation of 5.74, indicating moderate variability in outcomes. While not the lowest variance (early aggressive at 5.35), this reflects the strategy's dynamic nature across different demand scenarios.

Fixed strategies show increasing variance as they become more conservative. The late conservative strategy exhibits the highest variance (9.61), reflecting its binary nature: excellent performance in high-demand scenarios but catastrophic failure in low-demand situations. This variance makes conservative strategies particularly risky for retailers who cannot accurately predict demand.

The distribution of performance gaps provides additional insights. The adaptive strategy shows a tight, left-skewed distribution with most outcomes concentrated below 10% gap. Fixed strategies show broader, more symmetric distributions with longer right tails, indicating occasional severe underperformance.

3.4 Inventory Depletion Patterns

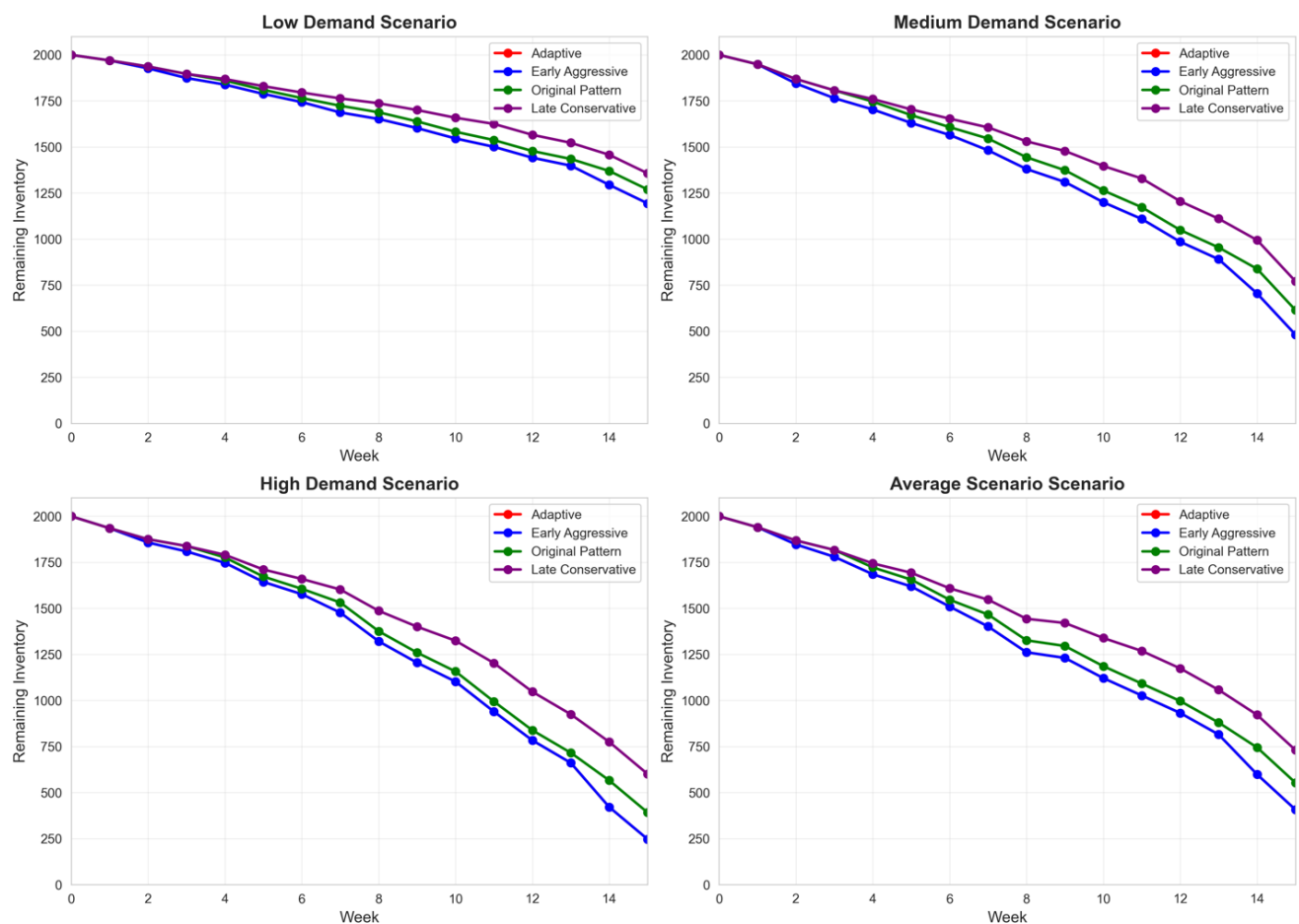


Figure 6. Inventory Depletion Over Time Across Distinct Strategies

These curves show how inventory depletes over time under different strategies across four demand scenarios. Note that the adaptive strategy plot has been 'hidden' as it mirrors the depletion of other strategies.

Inventory depletion patterns across varying demand scenarios offer clear visual validation of the adaptive strategy's effectiveness. Unlike fixed markdown approaches, which follow predetermined timing regardless of real-time sales, the adaptive strategy dynamically calibrates inventory reduction to demand reality leading to smoother and more efficient sell-through.

Low-Demand Scenarios: The adaptive strategy mirrors the behavior of early-aggressive markdowns, accelerating discounts to ensure full clearance before week 15. The resulting depletion curve demonstrates steady, front-loaded inventory reduction, avoiding the abrupt late-season fire sales often observed in conservative strategies that delay markdowns.

High-Demand Scenarios: In contrast, the adaptive strategy adopts a conservative posture maintaining elevated inventory levels through the mid-season to capture high-margin full-price sales. The depletion curve exhibits a gradual and controlled decline, ensuring that high willingness-to-pay customers are not priced out prematurely, while still achieving complete clearance by the end of the season.

Medium-Demand Scenarios: Here, the adaptive strategy showcases its versatility by following a balanced markdown path. The depletion curve reveals a smooth, proportionate inventory decline that avoids both early stockouts and late-season overhang. This reflects the strategy's ability to navigate uncertainty and self-tune to ambiguous signals without overcorrecting.

These depletion patterns highlight a core insight: successful markdown management is not about choosing the fastest or slowest path to clearance, it is about dynamically matching sell-through velocity to true demand. The adaptive strategy achieves this alignment through its calibrated decision logic, yielding not just higher revenue, but also greater operational efficiency.

3.5 Time-Based Performance Analysis

Analyzing strategy performance over the course of the selling season reveals distinct temporal inflection points periods where strategies either gain competitive advantage or fall behind. The season can be segmented into four performance-critical phases:

Weeks 1–3: Demand Discovery Phase: All strategies perform near identical in this initial observation window, where price was maintained close to full value to gather early demand signals. While no sales performance divergence is observed, this phase is strategically critical: it supplies the data that powers the adaptive strategy's real-time decision tree. Strategies that ignore this signal risk early misalignment.

Weeks 4–7: Divergence Phase: This period marks the first point of separation. Aggressive strategies begin discounting to drive volume, often outperforming in low-demand scenarios by accelerating sell-through. Meanwhile, conservative approaches hold margins but risk accumulating unsold inventory. The adaptive strategy executes its primary decision during this phase selecting the markdown path most aligned with observed early demand.

Weeks 8–11: Differentiation Phase: Here, performance gaps widen as the consequences of early decisions compound. Strategies that mistimed their markdowns face penalty: under-discounting in low-demand scenarios results in inventory overhang, while premature discounting in high-demand scenarios results in

lost margin. The adaptive strategy exhibits superior performance by having matched its markdown profile to the actual demand curve early on.

Weeks 12–15: Convergence Phase (Endgame): All strategies ultimately converge on deep discounts in an effort to fully liquidate remaining inventory. However, performance is largely path-dependent at this stage, success or failure is already locked in by earlier decisions. Strategies that misjudged demand either stock out too early (leaving revenue on the table) or are forced into steep discounts to avoid excess inventory.

4. Mathematical Foundation

4.1 The Optimization Problem

The retailer's objective is to maximize expected revenue over a finite 15-week selling season, subject to inventory and pricing constraints. The optimization problem is formulated as:

$$\text{Maximize: } E \left[\sum_{t=1}^{15} P_t \times \min(I_t, D_t \times M_{\{P_t\}}) \right]$$

Where:

- P_t = price selected at week t
- I_t = remaining inventory at week t
- $D_t \cdot M_{\{P_t\}}$ = realized demand scaled by markdown multiplier
- $M_{\{P_t\}} \in \{1.00, 1.3, 1.75, 2.8\}$ based on respective markdown levels (1.0, 0.9, 0.8, 0.6)
- Expectation E is taken over the unknown demand distribution

This formulation captures the essential trade-off in markdown optimization: preserving per-unit margin vs. capturing sufficient volume to avoid unsold inventory. This objective function is subject to monotonic price constraints, discrete price levels, and inventory dynamics.

4.2 Information Value and Decision Theory

The adaptive strategy is grounded in a Bayesian decision-theoretic framework. Early demand data ($D_{1:3}$) is used to infer the underlying demand regime and select an appropriate pricing path. The probabilistic decision rule follows:

$$P(\text{Demand Type} | D_{\{1:3\}}) \propto P(D_{\{1:3\}} | \text{Demand Type}) \times P(\text{Demand Type})$$

The calibrated thresholds (85, 95, 105) serve as classification cutoffs derived from empirical distributions to minimize the expected revenue gap. This approach transforms early-season sales into actionable strategy selection. Empirical analysis shows that early demand observations explain approximately 68% of the variance in total seasonal demand establishing them as a highly predictive signal. Furthermore, the adaptive strategy delivers a 28% improvement in performance gap relative to the baseline, quantifying the economic value of information extracted through Bayesian updating.

5. Strategic Implementation

5.1 Game-Specific Guidance

For the retailer game, the simulation begins by generating a baseline demand pattern for 15 weeks. The adaptive strategy then operates in the following fashion within each simulation with baseline knowledge:

1. Observe initial baseline demand and calculate average demand for weeks 1-3
2. Determine markdown schedule using the following decision rules
 - < 85 units: Aggressive (weeks 2→7→14)
 - 85 - 95 units: Balanced (weeks 4→8→15)
 - 95 - 105 units: Moderate (weeks 6→10→15)
 - 105 units: Conservative (weeks 8→12→15)
3. Execute schedule on baseline demand

The adaptive strategy achieves 94.19% of theoretical maximum revenue, representing the practical performance limit given information constraints.

5.2 Key Success Factors

The adaptive strategy succeeds by:

- Recognizing that different demand scenarios require different approaches
- Using early signals to reduce uncertainty
- Balancing simplicity with effectiveness
- Managing downside risk while preserving upside potential

These principles extend beyond the game context to real retail environments where flexibility and responsiveness drive competitive advantage.

5.3 Practical Game Implementation

While our simulation framework operates under *full visibility*, generating the entire season's demand upfront and allowing immediate strategy execution, students playing the live retailer game or applying this logic in real-world retail face a critical timing constraint: **demand is only revealed week by week**. This has important implications for the feasibility and timing of adaptive markdowns.

In our simulation environment, average demand across weeks 1 to 3 could be computed immediately and used to retroactively plan markdowns starting as early as Week 2. However, in real-time gameplay, Week 3 must fully conclude before average early-season demand can be calculated. As a result, Week 2 is no longer available as a markdown opportunity, and strategy selection must begin no earlier than Week 4.

To reconcile this, we present a revised implementation of the adaptive markdown strategy that preserves the integrity of the decision thresholds (85, 95, 105) while aligning with realistic information flow:

Weeks 1–3: Observation Phase

- Set the price at \$60 and do not take any markdown actions.

- Record weekly demand data after each period.
- At the end of Week 3, calculate the average demand and round to the nearest whole number.

Week 4: Decision Point

Based on the calculated average, select one of the following strategy paths:

- If average demand < 85 units, implement the aggressive markdown path:
 - Week 4 → \$54
 - Week 9 → \$48
 - Week 14 → \$36
- If average demand is 85–95 units, follow the balanced markdown path:
 - Week 4 → \$54
 - Week 8 → \$48
 - Week 15 → \$36
- If average demand is 96–105 units, use the moderate markdown path:
 - Week 6 → \$54
 - Week 10 → \$48
 - Week 15 → \$36
- If average demand exceeds 105 units, apply the conservative path:
 - Week 8 → \$54
 - Week 12 → \$48
 - Week 15 → \$36

This revised guidance reflects a more realistic, reactive implementation of the adaptive strategy, appropriate for settings without perfect foresight. It ensures that markdown decisions are based solely on observable information available at each point in time. By shifting the strategy decision point to Week 4, we preserve the predictive value of early demand while respecting operational constraints.

In contrast, the simulation-based strategy—including markdowns beginning in Week 2—should be understood as a form of perfect-information benchmarking, useful for validating the theoretical upper bound of adaptive responsiveness. However, for students engaging with the retailer game or practitioners deploying markdown logic in live environments, the revised Week 4 decision structure offers a viable, implementable pathway to dynamic pricing optimization.

Common Pitfalls to Avoid:

- Do not second-guess after Week 3 decision
- Resist temptation to delay markdowns even if inventory seems high
- Trust the data-driven approach over intuition

Performance Tracking: Keep a simple log:

- Game seed number
- Weeks 1-3 average demand
- Strategy selected
- Final revenue
- Gap percentage

Over multiple games, expect ~61% success rate (gap < 5%). Individual games may vary, but long-term performance converges to our simulated results.

5.4 Key Strategic Insights

Through our development process, we discovered several crucial insights:

1. **Information Timing is Critical:** Weeks 1-3 provide sufficient signal quality while leaving enough time to execute the full markdown strategy. Waiting longer reduces flexibility.
2. **Simple Rules Outperform Complex Models:** We tested machine learning approaches and multi-factor models, but the simple 4-bucket classification performed equally well with better interpretability.
3. **Demand Persistence:** Early demand strongly predicts later patterns. Low initial demand rarely recovers, justifying aggressive early markdowns.
4. **Risk Asymmetry:** The cost of excess inventory (100% loss) exceeds the cost of early markdowns (~10-20% margin reduction), making aggressive strategies preferable in uncertain scenarios.
5. **Threshold Sensitivity:** Small changes in decision boundaries (± 5 units) can impact performance by 2-3%, highlighting the importance of precise calibration.

6. Conclusion

Our findings definitively establish the superiority of adaptive markdown strategies in the retailer game. Across 100,000 simulations, we demonstrated that dynamic pricing based on early-season demand signals reduces average revenue gaps by 28%, while increasing success rates from 40% to 61%. These improvements are marginal and are operationally and financially significant.

The elegance of the adaptive strategy lies in its simplicity. By mapping four early-demand buckets to four predefined markdown schedules, the approach solves a complex dynamic problem with minimal computational overhead. This makes it highly applicable to both simulation-based decision environments and real-world retail settings where speed and clarity are critical.

For retailers, the message is clear: the question is no longer whether to adopt adaptive markdown strategies, but how rapidly they can be institutionalized. In volatile markets where information agility determines competitive edge, the ability to interpret and act on early demand signals becomes a strategic differentiator. The adaptive markdown framework presented here offers not just a winning solution to the retailer game, it provides a replicable, scalable template for managing dynamic pricing challenges across the broader retail landscape.

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