Pricing Pressure Index:

A New Framework for Measuring Consumer Price Sensitivity

A New Approach to Measurement

For more than a decade, Adobe has tracked the ebbs and flows of consumer behavior and the health of the broader U.S. digital economy through the Adobe Digital Economy Index and, more recently, our price sensitivity analysis. That analysis has historically relied heavily on a key signal referred to as trading down or consumers' preference for cheaper or lower-priced goods.

But this metric only tells part of the story. While changing levels of preference for cheaper goods have served well as proxy for understanding trends in price pressure, a more complete understanding of the importance of price to consumers also requires a measure of responsiveness to price changes.

This is why we're introducing a new, comprehensive framework: the **Pricing Pressure Index (PPI)**. The PPI balances two core dimensions of consumer behavior—the foundational metric of preference for lower-priced products (here defined as **Lower-Price Demand Concentration**) with responsiveness to price changes (what economists call **Price Elasticity of Demand**). Together, they provide a more holistic view and quantitative measure of the "pressure" exerted by price on consumer purchasing decisions.

PPI is built on Adobe's unprecedented scale of real-world transactional data—one trillion visits and 100 million SKUs across 18 categories—trusted by 85 of the top 100 U.S. online retailers. This breadth gives Adobe unparalleled insight into consumers' evolving ecommerce behavior and how they're navigating price and inflationary pressure in real time.

And this data reveals a clear inflection point: Right now, US consumers are experiencing the highest pricing pressure in at least a decade, not because prices keep rising, but because their ability to respond has collapsed. **Price Elasticity of Demand** is on the decline even as Lower-Price Demand Concentration persists. Consumers are still seeking the lowest-possible prices, but their ability to substitute or downgrade further is becoming increasingly limited.

The Metrics of Pricing Pressure

To ensure we're all reading from the same playbook, we define the key terms as follows:

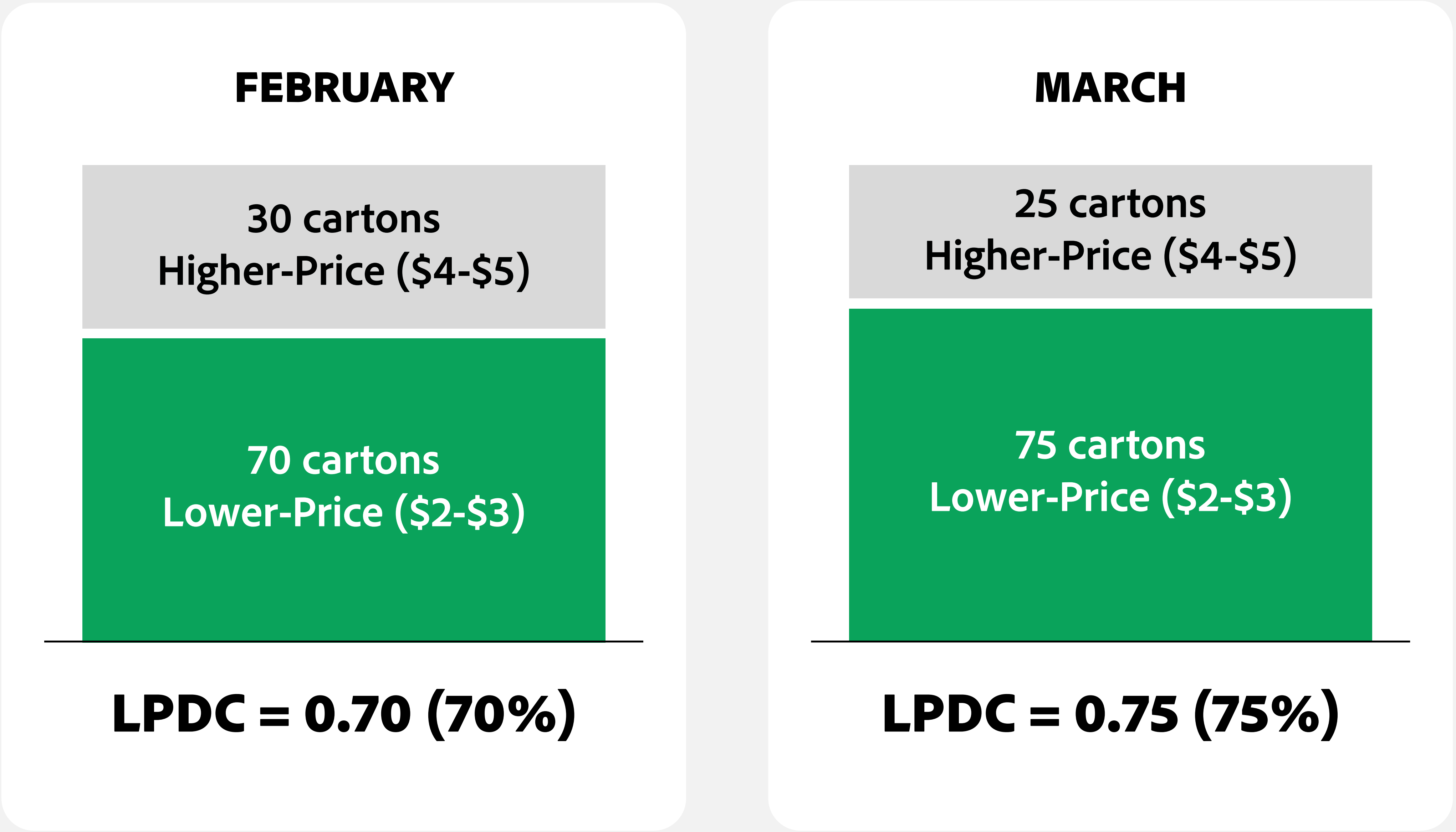
Pricing Pressure: Adobe's proposed measure of price sensitivity that indicates the overall importance of price to consumers in their purchasing decisions (i.e., the "pressure" that pricing exerts on consumers) across the entire U.S. online retail market. It's derived from a pair of sub-metrics: *Lower-Price Demand Concentration and Price Elasticity of Demand.*

Lower-Price Demand Concentration (LPDC): Adapted from prior analysis referred to as *trading down* or *de-premiumization*, LPDC captures the preference for lower-priced goods. We measure it by tracking the share of total demand concentrated in low-cost products, defined as the cheapest 50% of SKUs within a subcategory (i.e., eggs, TVs, makeup). While LPDC fluctuates month-to-month within categories, we aggregate these levels across all online retail categories to create a single monthly indicator of LPDC for the U.S. digital economy.

Example: Consider eggs with four distinct SKUs priced at \$2, \$3, \$4, and \$5. The two lowest-priced SKUs (\$2 and \$3) are classified as low-cost products. If 100 cartons are purchased in February and 70 of those are from low-cost SKUs, then LPDC is 0.7 or 70%. If another 100 cartons are purchased in March but 75 come from low-cost SKUs, then LPDC rises to 0.75 or 75%.

Lower-Price Demand Concentration (LPDC)

Measures the share of demand (% of units sold) captured by lower-price products.



Price Elasticity of Demand (PED):

PED measures how strongly demand responds to price changes. We estimate it by calculating the average effect of a 1% price change on demand, using daily price and demand changes compared to a rolling 30-day average for each SKU. These estimates are aggregated monthly to provide a comprehensive view of average PED levels across the U.S. digital economy.

Example: If a 1% increase in the price of a carton of eggs in February leads to a 1% decrease in demand, PED is 1. If another 1% price increase in March only leads to a 0.9% decrease in demand, then PED falls to 0.9.

Price Elasticity of Demand (PED)

The casual effect of a 1% change in price on demand for online retail products.

FEBRUARY

Price **+1%**

Demand **-1%**

PED = 1.0
(Unit Elasticity)

MARCH

Price **+1%**

Demand **-0.9%**

PED = 0.9
(Slightly Inelastic)

PED = % Change in Demand / % Change in Price

Estimating Price Elasticity of Demand

On the surface, PED appears to be a relatively straightforward metric to calculate but in practice it's never quite so simple. Price and demand influence each other and are both influenced by external factors.

Economics 101 teaches us that prices tend to rise when demand is strong and fall when demand weakens. In real world situations, both are further determined by a wide range of external forces such as seasonality, promotions, product availability, competitive dynamics, and broader economic conditions. As a result, it can be difficult to disentangle whether changes in sales are caused by changes in price or merely occur alongside them.

Traditional methods attempt to solve this problem by either carefully modeling potential influences on demand or by relying on tightly controlled price experiments.

While effective in narrowly focused experimental settings, these approaches do not scale well to the complexity and size of the online retail ecosystem and are not feasible with the available data.

To address this, we implemented a highly scalable **double machine learning** framework, building on recent advances in causal inference. This approach accounts for predictable patterns in both prices and demand driven by non-price factors.

By removing these influences, we can isolate the portion of demand change that is plausibly attributable to price alone. The resulting elasticity estimates reflect the average causal impact of price changes on consumer demand and can be aggregated consistently across products and time.

A detailed technical discussion of this implementation is provided in the appendix.

METHODOLOGY NOTE

Intensive Margin Bias

The nature of Adobe's online retail data, namely SKU-Day aggregations of actual online retail transactions, carries the limitation of being "conditional on sales". In simple terms, this means on days zero sales of a given product, no record is created. Since price, in our methodology, is derived from total revenue and units sold for a given SKU-Day record, we do not have visibility into the price of any given product on days with zero sales and thus lack visibility into dropout behavior. Our price elasticity estimations, as a result, only account for intensive margin—the change in quantity demanded, or how much more or less of a good is purchased—rather than whether a purchase will be made at all. There is a known bias in intensive margin price elasticity estimators toward lower elasticity estimates, especially when prices are high. This know bias, in addition to other factors discussed below, influenced our decision to interpret lower PED values as indicators of higher price pressure when LPDC is elevated.

Constructing the Pricing Pressure Index

The PPI combines LPDC and PED into a single, interpretable measure of how strongly price influences consumer purchasing decisions at a given point in time.

The index is built to reflect an important reality of consumer behavior: the relationship between price preference and price responsiveness is not constant. When demand is less concentrated in lower-priced products, price sensitivity tends to show up through stronger reactions to price changes. But when demand is already heavily skewed toward the cheapest options, declining elasticity no longer signals flexibility—it signals constraint. PPI is explicitly designed to capture this shift.

To combine LPDC and PED meaningfully, both metrics are first placed on a common scale so they can be compared and combined without relying on their original units. The transformation is anchored in historical behavior while allowing room for future extremes, ensuring the index remains interpretable even as consumer behavior evolves.

The normalized measures are then brought together using a nonlinear structure that changes how LPDC and PED contribute as conditions shift. At typical levels of LPDC, higher elasticity increases pricing pressure, reflecting consumers' willingness to adjust purchases when prices move. At elevated levels of LPDC, however, lower elasticity contributes more to pricing pressure, reflecting limited opportunities to substitute, downgrade, or delay purchases. This dynamic construction allows pricing pressure to continue rising even as elasticity declines.

Finally, the resulting series is indexed to January 2016, the earliest period for which both inputs are available. Framing the PPI as an index allows for clear comparisons over time, making it easier to contextualize today's pricing pressure relative to prior economic environments.

METHODOLOGY NOTE

Functional Form and Normalization

For readers interested in the technical construction of the index LPDC and PED are first normalized to a 0–1 range using pre specified upper and lower bounds. These bounds are chosen to include all observed monthly values over the past ten years, with additional buffer determined by each series' historical standard deviation. This design accommodates reasonable future extremes while maintaining stability and comparability over time.

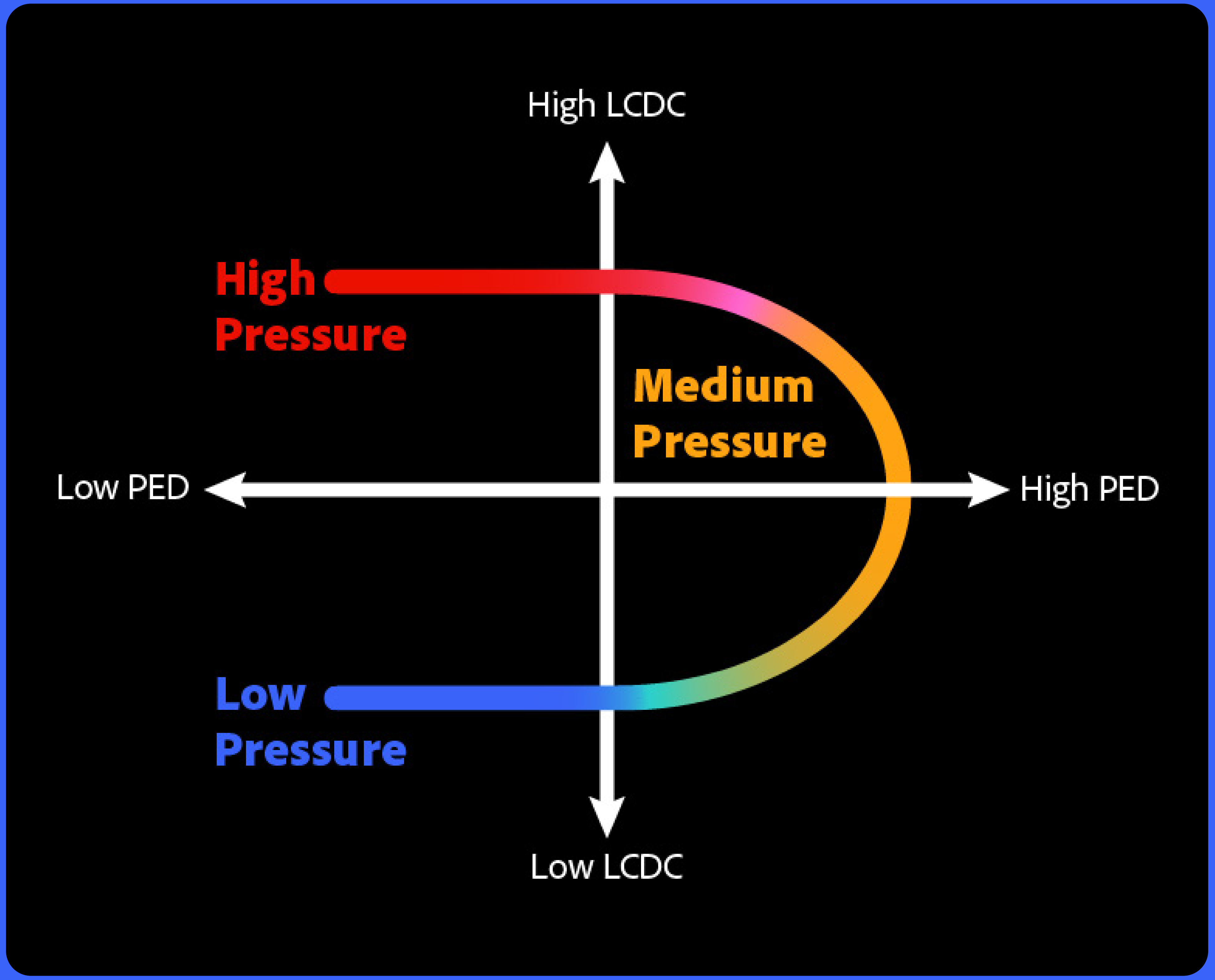
Let LPDC* and PED* denote the normalized values. The PPI is constructed using the following quadratic form:

$$PPI_t^{raw} = 2 \cdot LPDC_t^{*2} + PED_t^{*2} - 1.5 \cdot LPDC_t^{*} \cdot PED_t^{*}$$

This specification was selected to allow for **nonlinear interactions** between LPDC and PED. In particular, the negative interaction term ensures that at high levels of LPDC, lower PED values increase overall pricing pressure—reflecting substitution constraints and intensive margin bias in elasticity estimation—while at lower levels of LPDC, higher PED values raise the index.

The raw series is then indexed to January 2016 (=1.0) to produce the published PPI levels. Changes in the index therefore represent shifts in pricing pressure relative to the pre-pandemic baseline, not absolute elasticity magnitudes.

Interpreting the Pricing Pressure Index



By synchronizing LPDC and PED, the PPI provides a single, unified indicator of price sensitivity across the U.S. digital economy. It represents a continuous spectrum from **Low Pressure (PPI scale less than 1.1)** to **Medium Pressure (PPI scale of 1.1-1.6)** to **High Pressure (PPI scale greater than 1.6)** that can be visualized in three general stages. These thresholds were determined by separating the distribution of observed values over the past 10 years roughly into thirds:

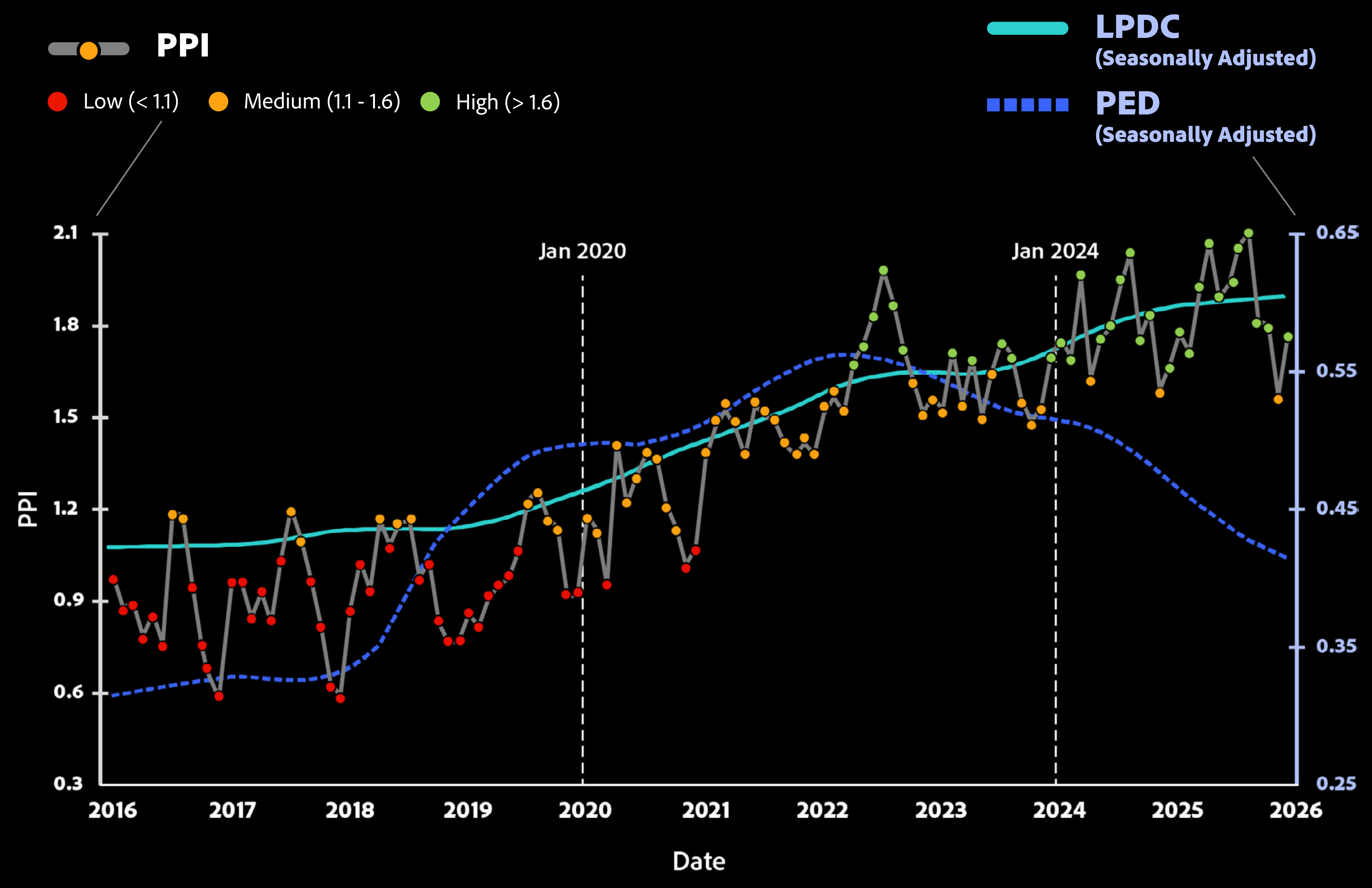
Low Pressure: Low PED, Low LPDC	In this stage, consumers take a quality-first approach to purchasing (low LPDC), showing comparatively low motivation to seek out the cheapest products or react strongly to price fluctuations (low PED).
Medium Pressure: High PED, Medium-High LPDC	In this stage, consumers still exhibit a relatively strong preference for lower-priced goods (high LPDC) but are still more willing to splurge when presented with attractive price cuts (high PED). Unlike the high sensitivity stage, they still have room to cut costs by downgrading to cheaper products and are quick to do so when prices rise.
High Pressure: Low-Medium PED, High LPDC	In this stage, consumers seek the lowest-priced products possible (high LPDC). With reduced discretionary spending, their options to 'trade down' have largely reached saturation and they are less likely to stretch to higher-cost goods even with significant discounts or deals (low PED). These limited opportunities for substitution, combined with a tendency for lower-price products to experience higher-than-average inflation, put further downward pressure on PED.

Why Can PED Fall While Pricing Pressure Rises?

Inflation tends to impact cheaper goods at a higher rate than more expensive products, and for the past decade has also more heavily affected non-discretionary categories (i.e., grocery, non-prescription drugs, medical equipment and supplies, pet products). With persistent high prices, demand naturally concentrates in these goods that inflate at higher-than-average rates. Once demand has concentrated in these products, opportunities for substitution and trading down when prices rise become increasingly constrained. The combination of these influences causes PED to decline as changes in demand become less proportional to changes price.

The conclusion we draw from this phenomenon is not that price has become less important to the consumer with the reduced responsiveness to price change. In fact, price is more important than ever in consumer decisions, but it is that very price pressure that locks demand into products that inflate at higher rates. We designed the PPI to account for this pattern, increasing as the underlying metrics swing toward the extremes. At lower LPDC, higher PED values contribute more toward increased PPI values, while at higher LPDC values, lower PED has a stronger effect on raising PPI values.

Pricing Pressure Index (PPI), LPDC & PED

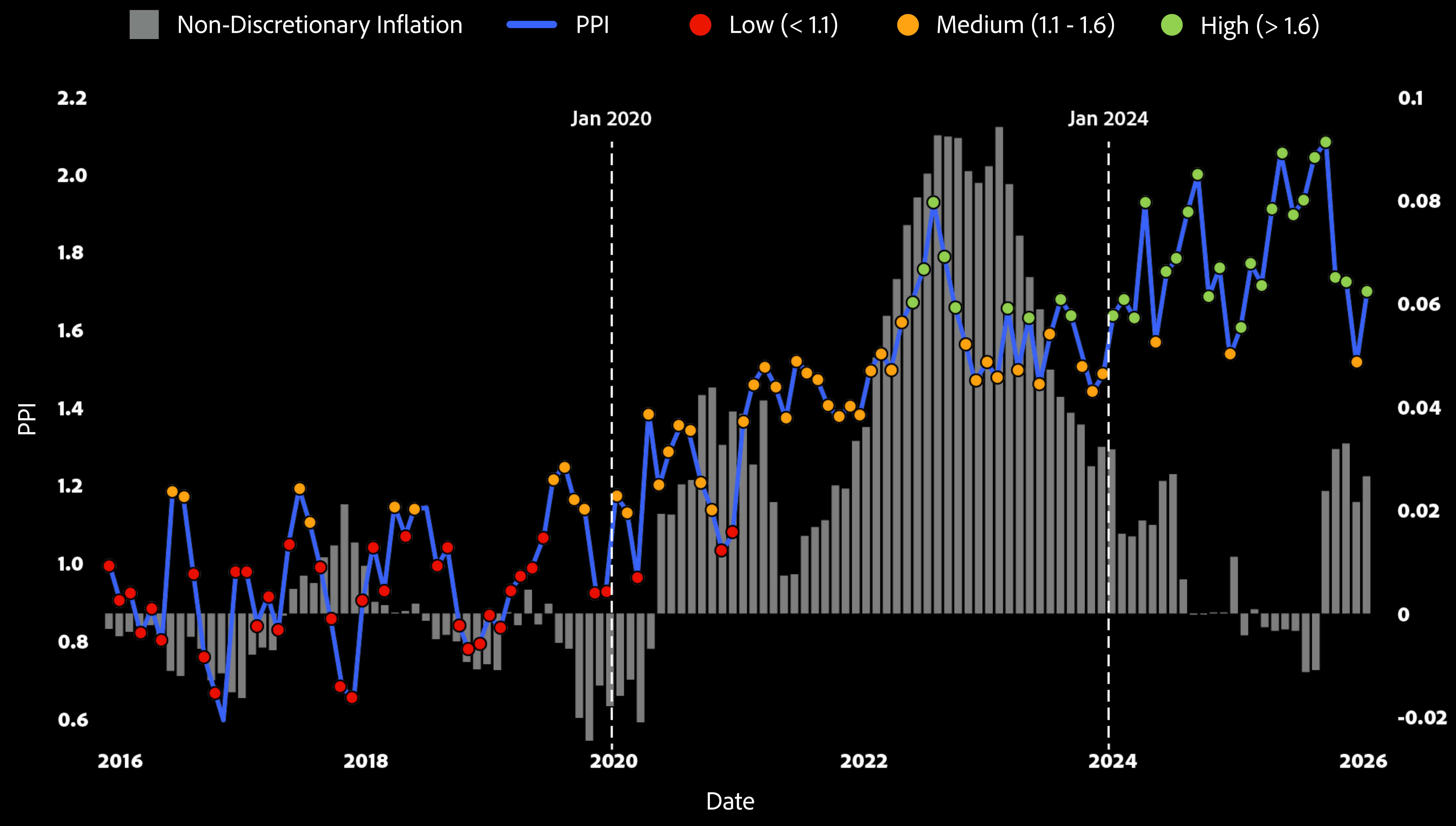


Pricing Pressure: A Decade in Review

When we survey the past 10 years (2016-2025), three distinct inflationary environments emerge: **Pre-Pandemic (2016-2019)**, **Pandemic (2020-2023)**, and **Post-Pandemic (2024-2025)**.

Across all 10 years, non-discretionary categories experienced higher inflation than online retail overall. This uneven inflation, coupled with the tendency of lower-priced products to inflate at comparatively higher rates, plays a critical role in driving consumer price sensitivity. Pricing Pressure can be roughly divided into these same three periods, each shaped by their inflationary environment.

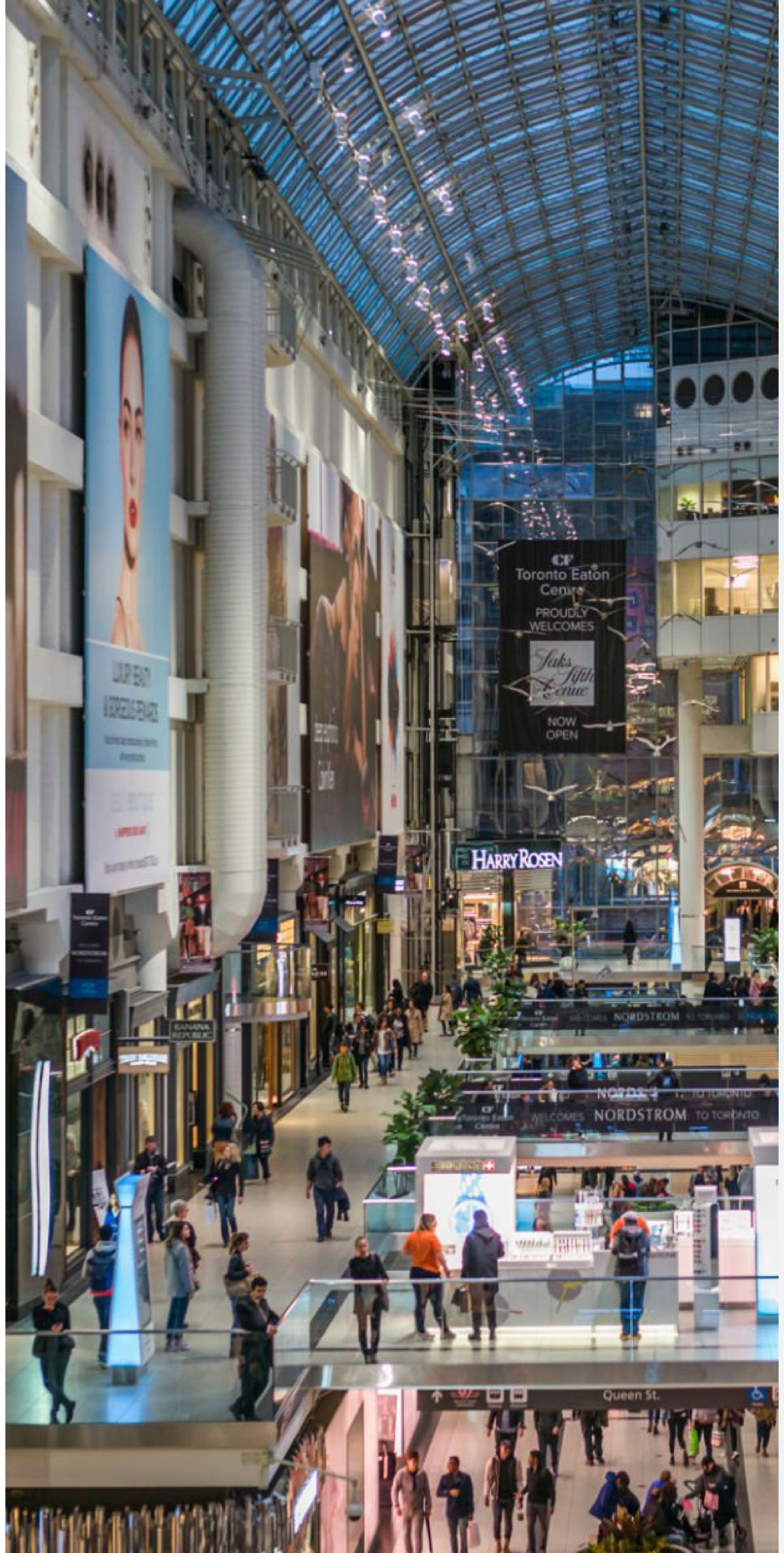
Pricing Pressure Index (PPI) & Non-Discretionary Inflation



Metrics	2016-2019	2020-2023	2024-2025
Topline Inflation	-3.7%	-0.3%	-2.8%
Non-Disc. Inflation	-0.4%	4.2%	1.1%
PED	0.95	1.28	1.14
LPDC	0.66	0.7	0.73
OPPI	0.96	1.46	1.8

Pre-Pandemic 2016–2019: Steady Deflation, Low Pricing Pressure

In the pre-pandemic period, online retail experienced consistent deflation. Topline online prices declined by an average of 3.7%, while non-discretionary prices declined by just 0.4%. Limited price pressure preserved low motivation for trading down (low LPDC) and comparatively smaller responses to price change (low PED) resulting in the lowest levels of price sensitivity observed over the past 10 years. Demand for the cheapest goods was much lower than today, with considerable flexibility to trade up or down in response to any inflationary movement.



PRICING PRESSURE IN PRACTICE

The following regimes describe pricing pressure environments across the U.S. digital economy in aggregate. Individual retailers may navigate meaningfully different levels of pricing pressure depending on category mix, customer demographics, and other factors.

Low Pricing Pressure

Low LPDC, Low PED

In periods of low pricing pressure, consumers show relatively little urgency around price. Demand is distributed across price tiers, and purchasing decisions are shaped more by quality, convenience, and product differentiation.

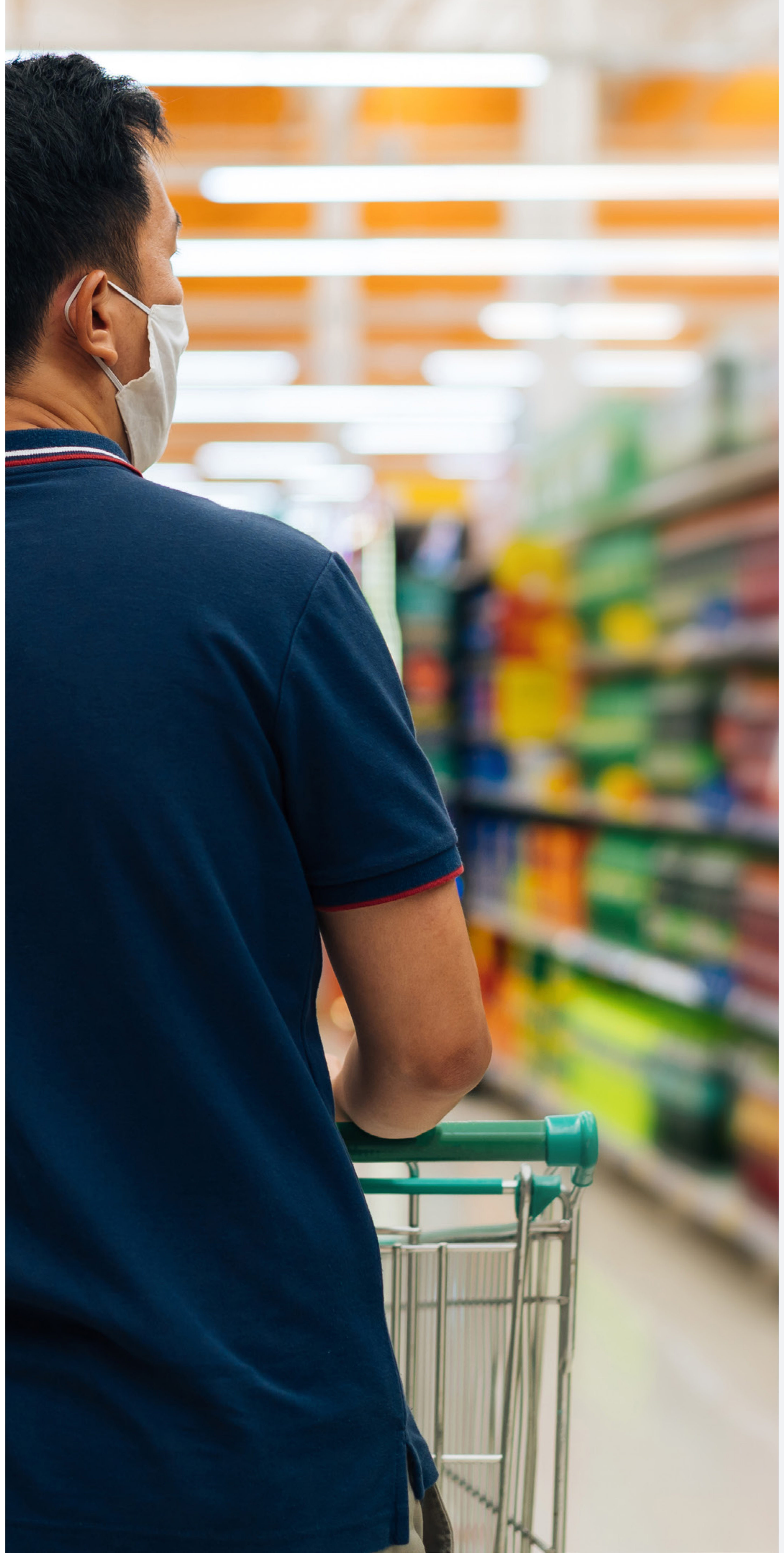
Event-driven promotions and seasonal category cycles (i.e., back to school, spring refresh) tend to translate more directly into discretionary spending and trade ups because budgets are less constrained.

What this implies for pricing strategy

Price is best treated as a positioning tool rather than a lever for volume. Retailers benefit most from competing on assortment, experience, and perceived value, using seasonal moments to highlight newness and premium features.

Pandemic 2020–2023: Inflationary Surge, Rising Pricing Pressure

During the pandemic, topline inflation averaged −0.3% despite a limited surge in 2022, but non-discretionary prices increased by an average of 4.2%. Demand for lower-priced goods increased considerably (rising LPDC), and consumers showed a strong response to price changes, though interest in higher-tier products persisted when presented with the right deal (rising PED). At this stage consumers still had room to move to lower-tier alternatives as necessary and proved quick to do so.



PRICING PRESSURE IN PRACTICE

Medium Pricing Pressure

Moderate–High LPDC, High PED

As pricing pressure builds, consumers become more deliberate. Demand increasingly concentrates in lower-priced products, but flexibility remains. Shoppers actively respond to price changes, trading down when prices rise and trading back up when promotions are compelling.

Seasonality remains an important driver, but it becomes more promotion sensitive: seasonal peaks still occur, yet a larger share of the lift is tied to deals, bundles, and sharp value messaging. In other words, “seasonal intent” is still there. Consumers still shop the calendar, but they express it more selectively and with tighter budget guardrails.

What this implies for pricing strategy

This is the phase where pricing decisions carry the greatest marginal impact. Promotions are highly effective, but precision matters. Clear value ladders and carefully targeted offers help retain customers during seasonal moments without accelerating margin-destroying trade downs.

Post-Pandemic 2024–2025: Persistent High Prices, High Pricing Pressure

From 2024 to 2025, topline prices again declined on average (–2.8%), but non-discretionary inflation remained positive at 1.1%. These price increases occurred on an already elevated base while demand was already heavily concentrated in lower-priced products, further constraining household budgets and driving up pricing pressure to it's peak—nearly double pre-pandemic levels. After several years of consistent growth, demand for cheaper products approached it's saturation point (high LPDC) with fewer and fewer opportunities to move to lower-tier alternatives and price elasticity quickly declined.

PRICING PRESSURE IN PRACTICE

High Pricing Pressure

Moderate–High LPDC, High PED

Under sustained pricing pressure, demand becomes heavily concentrated in the lowest priced products. Consumers are intensely price focused, but their ability to respond to further price changes is constrained. Even substantial discounts can yield diminishing returns, because many shoppers are already purchasing the cheapest viable options.

Seasonality does not disappear in this environment, but it expresses differently. Seasonal events may still bring traffic and intent, yet spending and product choice are more tightly concentrated in essentials, value tiers, and "needs-based" purchases. Seasonal lift and trade ups are still present, albeit more limited.

What this implies for pricing strategy

Traditional demand stimulation tactics lose effectiveness. Pricing strategy shifts away from "unlocking demand" toward maintaining stability—protecting availability and competitive pricing of low-price SKUs, preserving value perception, and prioritizing operational efficiency, even during seasonal peaks.

Takeaway

Retailers that move beyond one-dimensional price sensitivity and instead track both responsiveness and demand shifts will be better positioned to adapt pricing, optimize assortment, and stay competitive in a rapidly changing market.

Price Sensitivity is best understood through the dual lens of consumer price preference and responsiveness. Changes in elasticity and shifts toward lower-priced products each capture distinct aspects of how consumers experience pricing pressures, and their movements can diverge meaningfully as inflation, category dynamics, and substitution constraints evolve.

The Pricing Pressure Index provides a unified framework that brings these signals together. By jointly evaluating price responsiveness and demand concentration, the PPI offers a more balanced and consistent measure of price sensitivity, accommodating periods where consumers are highly price focused even as elasticity declines. This framework improves comparability over time and enables clearer interpretation of price sensitivity trends across changing economic environments.

In this sense, the PPI serves as a refinement and reframing rather than a redefinition of price sensitivity. It is designed to align established economic concepts with the realities of modern ecommerce data, offering a more complete view of how consumers respond to pricing pressure in practice.

Appendix: Estimating Price Elasticity of Demand Using Double MachineLearning

This appendix describes the methodology used to estimate price elasticity of demand (PED) from large-scale observational online retail data. The approach follows the Double / Debiased Machine Learning (DML) framework introduced by Chernozhukov et al. (2018) and the applied elasticity workflow described by Roemheld (2021), with adaptations for scalability.

1. Conceptual Framework

Observed prices and quantities are jointly determined by demand, retailer pricing strategies, seasonality, and other confounding factors. Naïve regressions of quantity on price therefore suffer from endogeneity and confounding. The DML framework enables consistent estimation of a low-dimensional causal parameter (price elasticity) in the presence of high-dimensional controls by combining machine-learning-based nuisance estimation with orthogonalized moment conditions and cross-fitting.

2. Data Structure

Observations are indexed by product SKU i and day t. Each SKU-day record includes units sold, price, and a high-dimensional feature vector capturing product attributes (name, brand, category, retailer, etc.), in addition to calendar effects, and historical sales, revenue, and price information. The dataset contains on the order of 20 million SKU-day observations per month.

3. Model Specification

We employ a partially linear regression (PLR) model:

$$\log(Q\_it) = \theta \cdot \log(P\_it) + g(X\_it) + \varepsilon\_it$$

Where Q_it denotes units sold, P_it denotes price, X_it is a high-dimensional vector of confounders, $g(\cdot)$ is an unknown nonlinear function, and θ is the price elasticity of demand. Identification relies on the assumption that, conditional on X_it, residual price variation is uncorrelated with the demand shock.

4. Nuisance Estimation and Cross-Fitting

Two nuisance functions are estimated:

- The expected log demand given covariates, $E[\log(Q\_it) \mid X\_it]$
- The expected log price given covariates, $E[\log(P\_it) \mid X\_it]$

These functions are estimated using a gradient-boosted decision tree model chosen for computational scalability. K-fold cross-fitting is employed: nuisance models are trained on K–1 folds and used to generate out-of-fold predictions on the held-out fold.

5. Orthogonalization and Elasticity Estimation

Residualized variables are computed as:

$$Y\sim\_it = \log(Q\_it) - \hat{g}(X\_it)$$
$$D\sim\_it = \log(P\_it) - \hat{m}(X\_it)$$

The elasticity parameter is then estimated via residual-on-residual regression:

$$\hat{\theta} = (\Sigma\, D\sim\_it \cdot Y\sim\_it) / (\Sigma\, D\sim\_it \cdot \log(P\_it))$$

This estimator is Neyman-orthogonal, ensuring robustness to first-order errors in nuisance estimation. In plain terms, this means it had been designed so that small errors in the models you use to control for other factors don't directly bias the final estimate. In other words the estimate is driven by the "unexpected" part of the data rather than by mistakes in predicting things like prices or demand. It's a robustness property: even if those auxiliary models aren't perfect, the main estimate remains reliable.

6. Zero-Sales Handling and Interpretation

Elasticities are estimated conditional on positive sales observations. As a result, the estimates capture intensive-margin price responsiveness—the change in quantity purchased among buyers. Conditioning on positive sales can bias elasticity estimates downward when prices rise because exit behavior is excluded. This bias is most pronounced following large price increases, not simply for intrinsically expensive goods. The dataset, while expansive, contains only SKU-Day aggregations of observed transactions, with price derived from daily revenue and units sold. The lack of pricing information for zero-sales occurrences constrained modeling options to only intensive-margin price responsiveness.

7. Intensive Margin Bias and the OPSI

The high likelihood that the downward bias inherent to our PED methodology would be most pronounced during periods that present other downward pressures on elasticity—namely periods with high LPDC and high inflation—helped inform the decision to design the OPSI estimator to interpret low elasticity as an indicator of high price sensitivity during periods of high LPDC. The downward pressure on elasticity estimates from both unobserved exit behavior and limited price responsiveness due to already high concentrations of demand in lower-priced products are both considered, in our estimation to be high-price-sensitivity indicators.

8. Aggregation

SKU-level estimates are aggregated to monthly category-level elasticities using within-category averaging. Category elasticities are then aggregated using pre-specified category weights representing an estimate of each category's share of the digital retail economy, producing a single topline elasticity estimate per month. The category weights used are identical to those used for topline inflation aggregation in the Adobe Digital Price Index.

9. Interpretation

The resulting elasticity estimates represent the causal effect of price changes on demand under the maintained assumptions. The DML framework allows for flexible confounder adjustment while preserving interpretability and scalability in large observational datasets.

References and Further Resources

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