Algorithmic Pricing and Consumer Price Sensitivity

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Abstract

Artificial Intelligence (AI) automates human decision-making. Algorithmic pricing—an AI application for scalable price determination—is now prevalent in ride-hailing, travel, drugs, gasoline, and online retail. A common thread across all these implementations is heightened price variability due to frequent price adjustments made by the algorithms. We study the impact of this algorithmic pricing-induced price variability on consumer behavior. Using granular clickstream data from a U.S. online grocery retailer that adopted algorithmic pricing, we show that increased price variability raises consumer price sensitivity and therefore partially offsets the gains typically attributed to algorithmic pricing. We corroborate these findings from the field through controlled lab experiments. We also identify factors that amplify or attenuate the effects of price variability.

Keywords: algorithmic pricing, price sensitivity, price variability, instrumental variables, e-commerce, artificial intelligence

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1 Introduction

$6.19 at 10:30 pm on Sunday, $6.39 at 3:28 am on Monday, $5.99 at 3:42 am, $2.99 at 4:28 am, $4.26 at 4:44 am, $3.99 at 8:40 am, and $4.47 at 12:21 pm. One may be forgiven for assuming these are prices for a stock listed on the stock exchange. However, these are the prices of a regular carbonated cola drink: seven distinct prices over the course of just two days in an online grocery retailer in the U.S. The price variation in this case is due to prices being set by algorithms. Given this context, we examine the following question — how does algorithmic pricing, characterized by dynamic price fluctuations, influence consumer behavior?

Artificial Intelligence (AI) has engendered the automation of decisions traditionally made by humans, extending significantly to the realm of algorithmic pricing, which is a machine-driven process to automate price determination (Brynjolfsson and McAfee, 2014). Initially a specialized feature of airline tickets (McAfee and Te Velde, 2006), it has now proliferated across sectors: ride-sharing platforms (Chen, 2016), online retail, travel and sports tickets (Cavallo, 2018), fuel (Assad et al., 2023), pharmaceutical drugs (Brown and MacKay, 2023), durable goods (Chen et al., 2016), and groceries (Aparicio et al., 2023).[1]

A defining feature of algorithmic pricing across implementations is the remarkably high price variability generated via frequent, small price changes — often thousands of updates daily. For instance, Brown and MacKay (2023) note that "algorithms facilitate both regular and more frequent [price] updates." Similarly, Assad et al. (2023) infer adoption of algorithmic pricing by gasoline stations by shifts in the "number of price changes made in a day" and Aparicio et al. (2023) note that "algorithmic pricing automates the pricing decision and enables firms to trigger an unprecedented number of price changes." In fact, firms that utilize algorithmic pricing are known to update prices very frequently, with Amazon changing prices approximately 2.5 million times a day, amounting to a price change for a product every 10 minutes on average (Business Insider, 2018); similarly, Aparicio et al. (2023) estimate 2 price changes per minute on AmazonFresh. Comparable trends are observable in "Smart Pricing" by Airbnb (Airbnb, 2017) and "Surge Pricing" by Uber, where prices change as frequently as every three to five minutes (Dholakia, 2015; Washington Post, 2015).

In this paper, we investigate how exposure to frequent price fluctuations driven by algorithmic pricing impacts consumer price sensitivity. We analyze granular clickstream

[1] See Aparicio and Misra (2023) for a recent review of AI and pricing.

data from a large U.S. online grocery retailer that implemented algorithmic pricing. A consequence of this implementation is that the algorithm frequently changes the price of thousands of products. Figure 1 provides examples of these highly frequent price changes. On average, roughly 1,200 products exhibit at least one price change per day. This data provides a unique opportunity to study the causal effects of algorithmic pricing for two reasons. First, we observe users' full sequence of browsing and purchase events over time, including price exposures even without purchase. In other words, we know what prices the consumers have seen across their visits (regardless of whether they buy or not). Second, the recurring nature of grocery shopping generates considerable individual variation in exposure to price changes for the same products. Our identification strategy exploits this variation by comparing the behavior of users who happen to be exposed to high versus low price variability for identical items at nearly the same time.

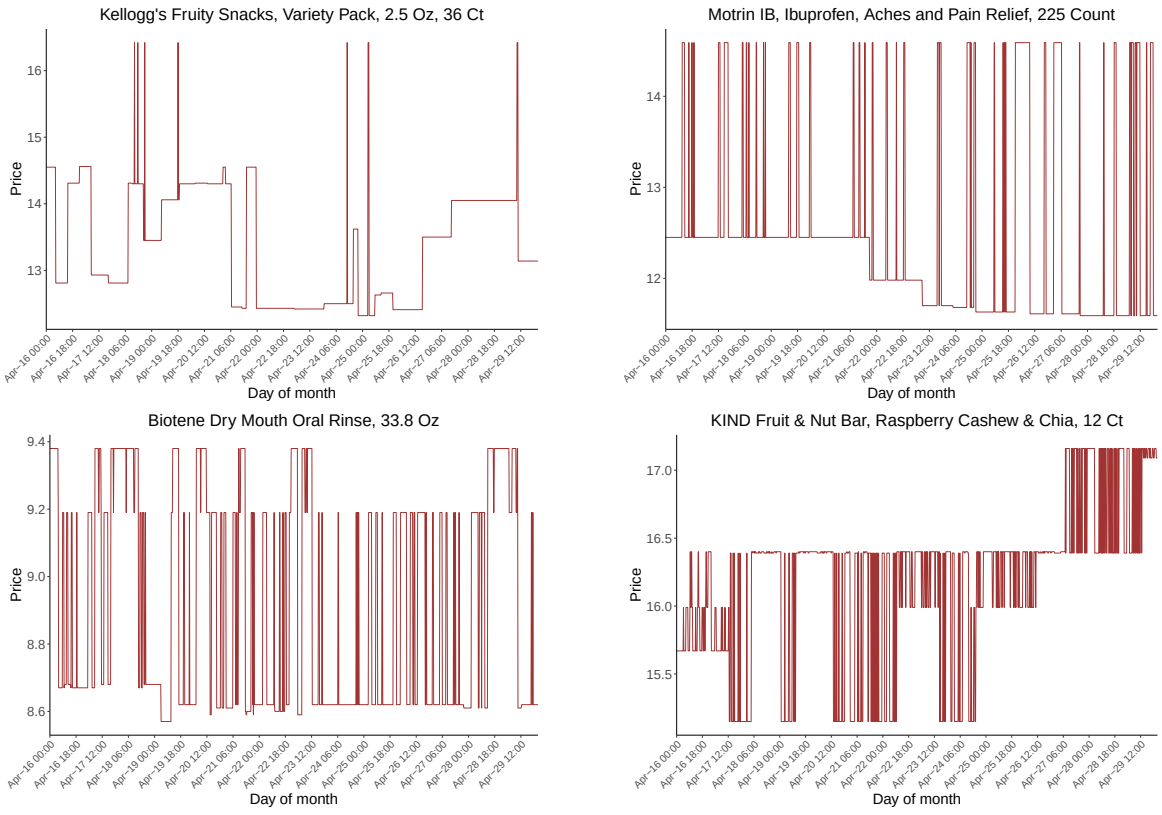


Figure 1: Algorithmic pricing on the online grocery platform

Our empirical strategy begins by constructing a measure that quantifies exposure to price variability. Our measure, which we denote as Price Variability Stock (PVS), tracks

the number of distinct prices a user sees for each product over time.[2] We then estimate the causal impact of differential user-level PVS on price sensitivity using a fixed effects model, controlling for unobserved user, product, and time heterogeneity. Importantly, prices are not customized in the platform, and thus exposure to price variability can be understood *as good as random* conditional on browsing intensity, inventory stock, and other rich behavioral features. We also use instrumental variables (e.g., prices that the customer did not see) and stress-test with different models and observation windows. Finally, we validate our main results using a simple pre-registered laboratory experiment. Throughout this set of empirical analyzes, we provide novel evidence that increased exposure to algorithmic pricing amplifies consumer price sensitivity.

From a managerial perspective, price sensitivity is a very consequential business outcome because it directly speaks of optimal markups. The canonical Lerner rule links the profit-maximizing price–cost margin to the elasticity of demand, implying that a more price-sensitive demand leads to lower markups and, consequently, lower profits (Salinger and Ampudia, 2011; Cohen et al., 2021). Beyond its implications for existing products, changes in price sensitivity can influence a broader set of strategic decisions. For instance, if exposure to price variability spreads across products, it can affect how consumers respond to newly introduced product.

Taking a step back, algorithmic pricing systems are typically deployed under the assumption that consumer demand is stable while firms experiment with prices to learn the profit-maximizing price. However, our findings reveal a potential boomerang risk: the process of frequent price adjustments may itself alter consumer behavior. By repeatedly exposing consumers to fluctuating prices, algorithmic pricing can increase the salience of price and make consumers more responsive to price changes. As a result, the pricing system may inadvertently undermine its own objective—prices that appear optimal based on historical demand estimates may no longer remain optimal once consumers' price sensitivity evolves in response to repeated exposure to price variability. These findings speak directly to the literature on price experimentation and demand learning (Aghion et al., 1991; Li et al., 2015), which implicitly treat demand as an object to be learned rather than one that can itself be shaped by pricing policies (Handel and Misra, 2015; Misra et al., 2019; Jain et al., 2024; Holtz et al., 2025). For managers deploying AI-driven pricing tools, our findings imply that pricing algorithms need to account for behavioral feedback effects when designing price experimentation and learning strategies.

[2]The name derives its inspiration from the marketing literature where researchers record the total number of exposure to ads for the same brand in a variable called the Advertising Stock (Erdem et al., 2008a; Shapiro et al., 2021).

Related Work

Despite the increasing adoption of algorithmic pricing, there is a limited understanding of consumer reactions to the high price variability it creates. Existing research primarily focuses on the supply-side implications of AI-based pricing. Miklós-Thal and Tucker (2019); Calvano et al. (2020); Brown and MacKay (2023); Hansen et al. (2021) show that price algorithms can learn from each other and potentially arrive at collusive, supra-competitive prices. Further, algorithmic pricing can trigger reactions from sellers and buyers in platform-like settings. Castillo (2020); Angrist et al. (2021); Cohen et al. (2022b) study drivers' and riders' strategic responses to surge pricing in ride-hailing. In a similar vein, Huang (2021) studies hosts' (sellers') responses to Airbnb's "Smart Pricing" tool, and Zhang et al. (2021) documents racial heterogeneity in the adoption of such pricing tool across hosts. To our knowledge, no prior work has studied user-level exposure to algorithmic pricing and how that impacts consumer behavior. Our paper extends this literature by first devising individual-level measures of exposure to algorithmic pricing (PVS, described earlier) and then empirically demonstrating how that shapes a core construct of consumer behavior, namely price sensitivity.

Our work contributes to a broader discussion about the interplay between AI pricing and behavioral sciences. Haws and Bearden (2006) and Weisstein et al. (2013) show that unusual price differences may evoke feelings of unfairness and thereby reduce willingness to pay. These findings, obtained in laboratory experiments, prompt researchers to investigate "realistic shopping environments and under conditions of higher involvement" (Haws and Bearden, 2006). More recently, Cohen et al. (2022a)'s theoretical framework inputs fairness constraints to optimize pricing. Finally, although not in the context of algorithmic pricing, Rotemberg (2005); Anderson and Simester (2010) have shown that price changes can trigger customer antagonism. All in all, price variability may interplay in various dimensions with consumer behavior. Our work uniquely contributes to this debate by reporting novel field about the intersection of AI pricing and consumer behavior.

With this research gap in mind, price sensitivity remains a fundamental question of interest. Extant studies have primarily used weekly scanner data to estimate households' inter-temporal choices and price policy changes, such as own-price and cross-price elasticities or responses to temporary and permanent price changes. These include both reduced-form models (Gupta, 1988; Chintagunta, 1993; Boulding et al., 1994; Mela et al., 1998; Swait and Erdem, 2002; Pauwels et al., 2002; Elberg et al., 2019) as well as structural models (Hendel and Nevo, 2004; Erdem et al., 2008a). We contribute to these studies

in multiple ways. First, scanner or homescan datasets record purchases but not visits. A key feature of our data is our ability to see consumer-level exposure to prices, even when the consumer does not purchase anything. These logs are critical since over 80% of the PVS comes from user visits only, i.e., visits without any purchases. Said differently, offline settings may fail to capture what products and prices a given customer is browsing. Moreover, scanner panels often impute the weekly volume-weighted average price, rather than the actual price that the consumer observes (Aparicio et al., 2023). Finally, offline retailers rarely employ algorithmic pricing. Consequently, price changes are sparse, making the investigation of price variability induced by algorithmic pricing not ideal to study.

Price Variability and Price Sensitivity

Before continuing with the empirical analyses, it is helpful to discuss that the effect of algorithmic pricing on consumer price sensitivity is theoretically ambiguous. On one hand, frequent price adjustments may heighten price salience. A large literature on consumer choice and bounded rationality links salience to stronger behavioral responses to prices (Chetty et al., 2009; Bordalo et al., 2020; Blake et al., 2021). Much like flashing billboards that capture visual attention, continuous price changes may draw consumers' focus to price and lead them to overweight it in purchase decisions (Krider et al., 2001; Folkes and Matta, 2004). Return to Figure 1: a consumer repeatedly exposed to such price fluctuations may become increasingly attentive to price movements.

Furthermore, algorithmic pricing may influence the formation of reference prices.[3] Reference prices are typically anchored on previously observed prices, advertised deals, or category benchmarks (Vanhuele and Drèze, 2002; Mazumdar et al., 2005; Jindal and Aribarg, 2021). However, when prices change frequently, consumers may find it difficult to rely on stable historical anchors. Because memory for past prices decays quickly (Jonides et al., 2008), consumers may rely disproportionately on the most recently observed price. In such environments, each new price observation can trigger stronger reactions to price changes. Taken together, heightened salience and unstable reference prices suggest that frequent price fluctuations could *increase price sensitivity*.

On the other hand, ubiquitous variability due to algorithmic pricing could "jam" the signal of good or bad deals. In contrast to traditional Hi-Lo pricing strategies, which create salient high and low price benchmarks (Ellickson et al., 2012; Hitsch et al., 2021),

[3] A large literature documents how reference prices are formed and how firms influence them through price presentation and framing strategies (Kalyanaram and Winer, 1995; Amaldoss and He, 2018).

algorithmic pricing may generate complex and noisy price paths. Again, as per Figure 1, a consumer exposed to many distinct prices over a short period may find it difficult to infer what the "typical" price should be.

Consistent with this possibility, prior research documents that consumers exhibit limited price recall and operate with "limited cognitive resources" (Deck and Jahedi, 2015). Excessive variability may therefore reduce the informational content of price signals and expand consumers' range of acceptable prices (Lichtenstein et al., 1993). Over time, repeated exposure to fluctuating prices may also lead to habituation, whereby consumers become accustomed to frequent price changes and respond less strongly to them (Rankin et al., 2009). In the words of Wathieu (2004), "things experienced for a long time lose value (habituation)." Rather than forming a single reference price, consumers may instead develop a diffuse distribution of reference prices. As a result, consumers may recall incorrect price ranges or even "phantom prices" when evaluating subsequent offers (André et al., 2022). These mechanisms suggest that algorithmic price variability could *decrease price sensitivity*.

As firms increasingly adopt AI-driven pricing systems, there is limited guidance on whether the resulting price variability ultimately strengthens or weakens consumers' responsiveness to price. Understanding this behavioral response is therefore critical for evaluating the broader implications of algorithmic pricing.

2 Data and Empirical Setting

We collaborate with an online retailer in the U.S. that implemented algorithmic pricing on its platform. The data covers thousands of products across a wide range of categories, subcategories, and price ranges. Additionally, it includes clickstream records at the user level, which allows us to observe the entire sequence of the visitation activity (e.g., search queries, product views, add-to-carts, and orders placed).

This data is empirically valuable compared to scanner panels which ignore visits (i.e., price exposure) that do not end with a purchase. Moreover, the recurring nature of groceries and related products renders them ideal for exploiting multiple visitations over time—creating various degrees of price exposure across consumers throughout their visits. Table 1 provides a brief overview of the data.

Table 1: Data Description

Summary Statistics	
Consumers	784,190
Products	3,039
Product-Sessions	21,194,749
Time period	14 months (2018/June to 2019/July)
Median price	$8
Top-5 categories	Household Supplies, Baby, Health & Beauty, Grocery, Pet Supplies

3 Stylized Facts of Algorithmic Pricing

We begin our empirical analysis by presenting three key stylized facts of algorithmic pricing. These facts help build intuition for our identification strategy. Moreover, they provide a broader perspective of pricing algorithms at the scale of thousands of products in online retail. These facts focus on a central tenet of algorithmic pricing—price changes—and characterize their (1) frequency, (2) magnitude, and (3) exposure.

Fact 1: Price changes are extremely frequent

Figure 2 (and Figure 1) illustrates a striking degree of price variability over time. The graph overlays three months of price levels at 15-minute intervals. It makes evident that prices consistently fluctuate throughout the days of the month and hours of the day. For a typical product, the probability of a daily price change is roughly 40%, and often prices will change several times within the same day. On a typical day, ∼1,200 products (out of 3,039 in our sample) change price at least once. These are remarkable frequencies of price changes, compared to standard benchmarks in the literature (Cavallo, 2018; Aparicio et al., 2023).

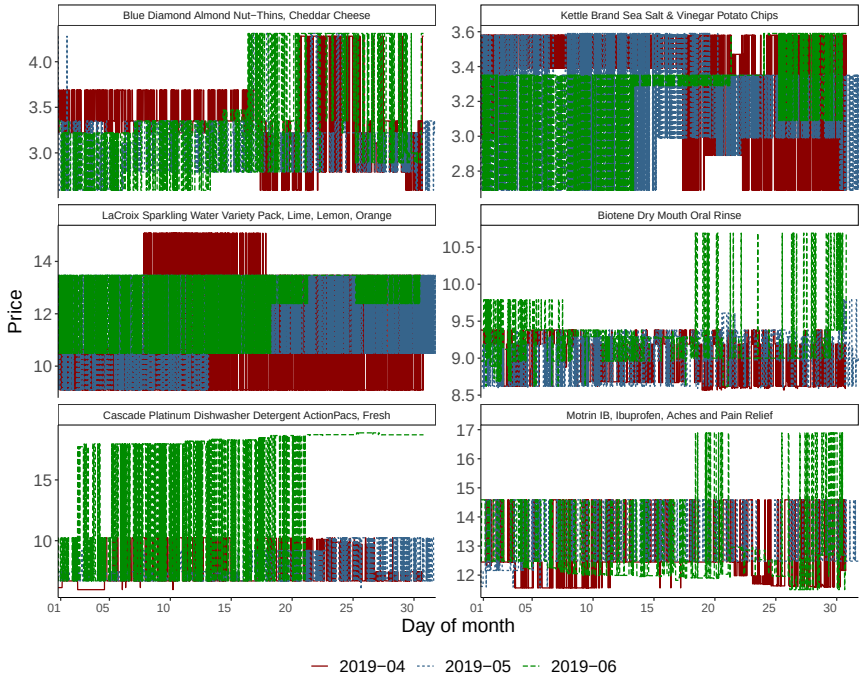


Figure 2: 15-Minute prices across days of the month

Fact 2: Price changes are small but not trivial

Algorithmic price changes are frequent and small but noticeable. Figure 3 shows the distribution of price changes in absolute percentage terms across products. A quarter of the price changes are lower than 5% of the previous price, and roughly 70% of all price changes are within 20%.[4] In dollar terms, the average price change is \$1.2 and the median price change is \$0.65. Furthermore, more than 60% of all changes include a change in the left-most digit (e.g., changing price from \$3.99 to \$4.09), which is likely to make them more noticeable for consumers (Thomas and Morwitz, 2005).

Fact 3: Price changes are not predictable—in direction or timing

Price changes occur extremely frequently (Fact 1) and are economically noticeable (Fact 2). However, predicting price changes is almost impossible for consumers. Panels (a) and (b) of Figure 4 show that price changes occur throughout all days of the week and hours of the day, respectively.

What does this price variability imply? Panel (c) shows that the time difference between the visitation and the closest price change is symmetric: a customer is equally likely to visit the platform before or after the closest price change. In addition, Panel (d)

[4]In subsequent econometric analyses, we only consider price changes where either the price has changed by more than 5¢ or the left-most digit has changed.

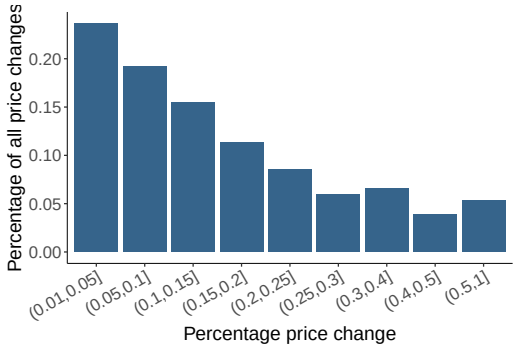
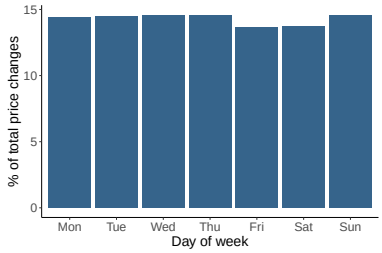
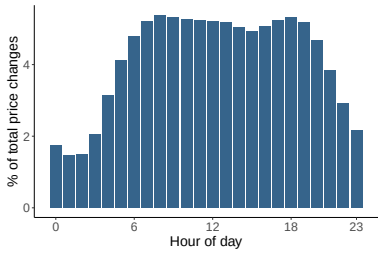


Figure 3: Cumulative distribution of price changes

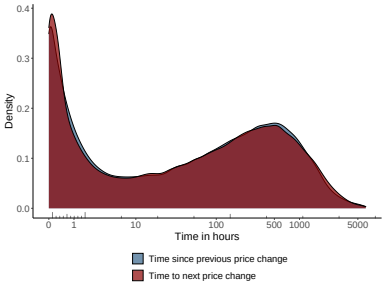
shows that a customer is equally likely to face a price increase or a price decrease, as the price difference before and after the most immediate visit is symmetric with respect to the median price in the month. Appendix A provides alternative measures that are overall consistent with these figures.



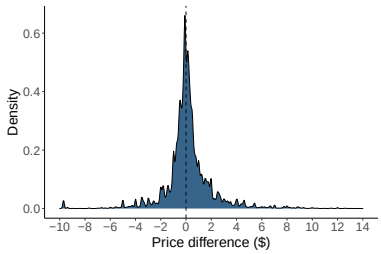
(a) Price changes by day of week



(b) Price changes by day of week



(c) Distribution of time of price changes before and after user visits



(d) Distribution of magnitude of price changes before and after user visits

Figure 4: (Un)Predictability of price changes

In summary, we observe a "haphazard" visitation pattern: customers are exposed to price changes as random insofar as the prices that they encounter are sometimes the same, higher, or lower. Algorithmic pricing makes it infeasible for customers to predict what price change they will experience on their next visit, either in direction or in magni-

tude. We acknowledge that while users' decision to visit the platform is not random, their haphazard visitation patterns imply that their *exposure to price variability*, conditional on their visitations, can be considered *as good as random*. These stylized facts collectively provide useful groundwork for the user-level models of price sensitivity and for constructing relevant instruments.

4 Consumer Exposure to Price Variability

We estimate the impact of algorithmic pricing on price sensitivity by exploiting the exposure each user has to price variability. What does "exposure" mean in this setting? To see this, it helps to begin with a model that bears resemblance to studies investigating the "stock" of advertising (Erdem et al., 2008b; Shapiro et al., 2021). Consider three consumers, A, B, and C who visit one product four times during the same week, as shown in Figure 5. Because prices are not personalized and tend fluctuate frequently, a given consumer may end up seeing a different number of unique prices for the same product over the same time period. Consumer A sees two unique prices, B sees three prices, and C sees four prices. We will utilize such differential exposure to prices for the same product as our key measure of exposure to price variability. We tabulate this exposure to multiple unique prices for a given user–product–time combination in a variable defined as Price Variability Stock (PVS). Thinking of algorithmic pricing through the lens of advertising is helpful—like advertising, where multiple ads matter, the intensity of price variability exposure also matters.

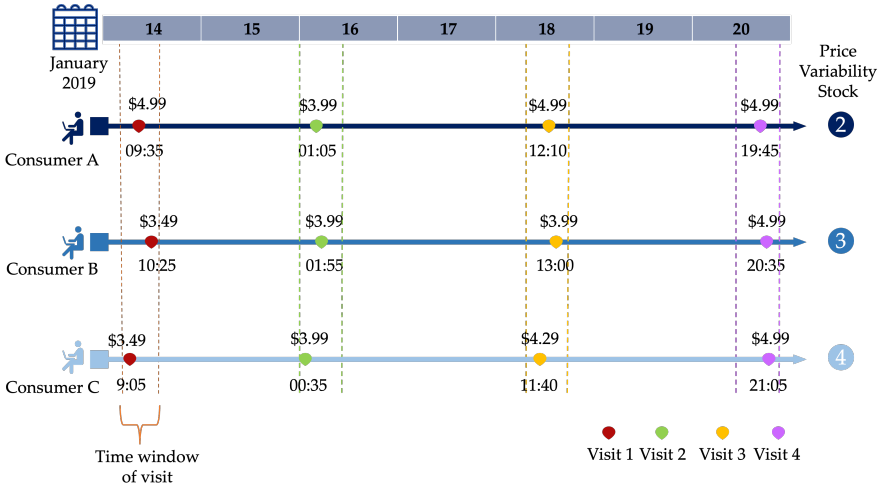


Figure 5: Illustration of price variability exposure for different consumers

With this context in the background, we define our user-level model as follows:

$$Y_{ijt} = f(P_{ijt}, PVS_{it}, X_{ijt}; \epsilon_{ijt}) \tag{1}$$

where Y_{ijt} is the number of units of product j purchased by user i during shopping session t and P_{ijt} is the price of product j. PVS_{it} is the price variability stock described earlier, operationalized as the number of unique prices that the consumer has seen over the past L days. Note that PVS_{it} is aggregated over all products the consumer browsed more than once to account for cross-product spillovers.[5] X_{ijt} are a rich set of time-varying covariates that account for user i's historical search intensity and the size of their inventory based on past purchases. Throughout, we report estimates for $L = 30$ days but the results are similar for $L \in \{15, 60\}$ days (Section 7).

To measure the impact of algorithmic pricing on price sensitivity we estimate the following econometric specification:

$$\begin{aligned}\log(\mathbb{E}[Y_{ijt}|X]) =& \beta_0 + \beta_1 \log(P_{ijt}) + \beta_2 \log(PVS_{it}) + \boldsymbol{\beta_3} \log(P_{ijt}) \times \log(PVS_{it}) \\ &+ \delta X_{ijt} + \Gamma_i + \mu_j + \tau_w\end{aligned} \tag{2}$$

where β_1 captures the baseline price sensitivity, β_2 captures the effect of PVS on demand, and β_3 captures the relationship between the PVS and price sensitivity. A negative value of β_3 indicates that consumers become more price sensitive after increasing exposure to algorithmic pricing-induced price variability. Γ_i denotes user fixed effects, μ_j is product fixed effects, and τ_w is year-week fixed effects. X_{ijt} are user and product-level time-varying covariates. Since the model is at the user-product-session level, Y_{ijt} has a large mass at zero as most sessions end without any purchase. To account for this, we estimate the model using a Quasi-Poisson Likelihood. Section 7 reports robustness specifications.

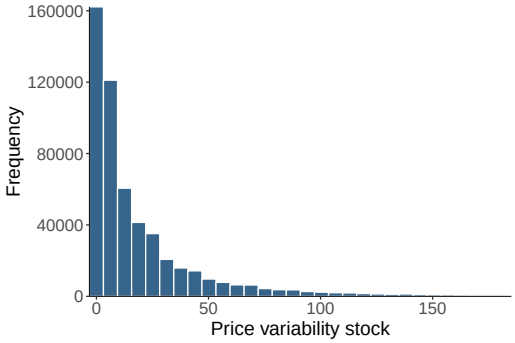
4.1 Identification Strategy

One may argue that PVS_{it} is not randomly assigned but rather determined by the user's search process. For instance, a given consumer who tends to search more may intrinsically be more price sensitive and hence may repeatedly visit the retailer's website to fetch a good deal. As a consequence of their repeated visits, they get exposed to different prices

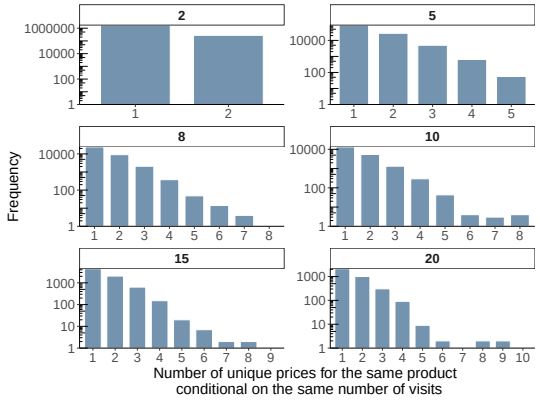
[5] To illustrate: if consumer i visited the product page for Nutella thrice in the past 30 days and saw two different prices, and visited the page for Diet Coke once and hence saw one price, then PVS_{it} is two (i.e., Diet Coke does not contribute to the PVS.

for the same product, and therefore the effect that we pick up is an artifact of browsing intensity and not necessarily a change in behavior. However, the rich clickstream data allow us to flexibly control for time-varying browsing and purchase intensities. The controls remove these concerns: the effect is identified using variation in PVS_{it} that is conditional on the number of product visits, the number of browsing sessions, and the number of previous purchases. In other words, the effect captures the variation within users, conditional on visiting the product the same number of times.

Figure 6 provides evidence that there is meaningful variation in conditional PVS_{it}. Panel (a) shows the marginal distribution of PVS aggregated at the user-visit level, i.e., the level at which Model 2 is estimated. Panel (b) shows the conditional distribution of price variability stock at the user-product-visit level. Consider the top-right facet of Panel (b): conditional on visiting a product five times in the past 30 days, some users were exposed to five prices, while others just one price. This variation allows us to remove the role of the browsing intensity, i.e., estimates of Model 2 are conditional on visiting the same product the same number of times. Furthermore, user- and product-fixed effects control for unobserved time-invariant user and product heterogeneity, respectively.



(a) Marginal distribution of PVS



(b) PVS conditional on the number of visits to a given product in the past 30 days

Figure 6: Variation in PVS across users

Additionally, there may be concerns about potential strategic behavior. For example, users could be actively seeking out lower prices and hence may have learned to visit at certain times of the day when they expect prices to be lower. While this is a valid theoretical argument, there is little empirical evidence in its favor. Recall the stylized facts of algorithmic pricing from Section 3, where we show that user visitation timing is "haphazard", i.e., users visit at different times during the day across visits and have limited

ability to predict price changes. Nevertheless, since we observe the actual timestamp of a user's visit to a particular product, in our main specification we control for day of the week and hour of the day. These controls along with the stylized facts ameliorate any concerns regarding the strategic visitation from consumers.

4.2 Estimation Results

Fixed Effects Models

Table 2 shows the results from the Quasi-Poisson estimation of Model 2, which includes a rich set of controls and fixed effects. The coefficient in the first row represents the baseline price sensitivity. The key coefficient of interest, i.e., the interaction between price variability stock and price is shown in the second row. Recall that a negative significant coefficient on this variable indicates an increase in price sensitivity when users are exposed to more number of unique prices for the same product. This is exactly what we find. Price elasticity in the model equals $-1.26 - 0.065 \log(PVS)$. Thus, doubling the price variability stock increases the magnitude of price elasticity by $0.065 \times \log(2) = 0.045$, corresponding to a 3.6% increase relative to the baseline elasticity.

Table 2: Exposure to higher price variability increases price sensitivity: Quasi-Poisson model with fixed effects

Dependent Variable:	Units	
Model:	(1)	(2)
Variables		
Log price	-1.26***	-1.26***
	(0.061)	(0.061)
Log price x Log price variability stock	-0.065***	-0.065***
	(0.007)	(0.007)
Log price variability stock	0.149***	0.151***
	(0.015)	(0.015)
Log # of prior purchases	-0.443***	-0.441***
	(0.009)	(0.009)
Log # of visits	0.184***	0.182***
	(0.013)	(0.013)
Log # of products viewed	0.222***	0.219***
	(0.005)	(0.005)
Fixed-effects		
User	✓	✓
Product	✓	✓
Year week	✓	✓
Day of week		✓
Hour		✓
Fit statistics		
Observations	21,194,749	21,194,749
Pseudo R^2	0.240	0.240
Log-Likelihood	-4,391,172.3	-4,389,822.9

*The table reports Quasi-Poisson estimates of Model 2. Each observation is at the user-product-visit level and the dependent variable is the number of units of the product purchased by the user. Both columns show estimates from a fixed effects model with time-varying controls. Column (2) additionally controls for day-of-week and hour-of-day fixed effects. The first row is the baseline price sensitivity and the second row shows the coefficient of interest, i.e., the interaction between (log) price and the (log) PVS. Clustered (User & Product) standard errors are shown in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Columns 1 and 2 include controls for time-varying users' propensity to search and the state of their inventory based on past purchases. The time-varying controls are calculated using a 30-day rolling window looking back from the date of the session. The fixed effects account for time-invariant user and product unobserved heterogeneity. As mentioned previously, we may still speculate about users timing their visits when price changes, especially price decreases, are likely to happen. However, we account for this by directly controlling for the day and time of the visit. Column 2 of Table 2 includes day-of-week and hour-of-day fixed effects to account for differences in propensity to visit at different times. The results are unchanged; price sensitivity increases when exposed to higher price

variability caused by algorithmic pricing.

Instrumental Variables—Control Function Approach

Next, we address concerns of potential systematic biases in users' observed PVS_{it} by exploiting exogenous price variability that is directly related to PVS_{it}. This strategy implicitly exploits the variation in the timing of a user's visit to the website. Specifically, the exact time a user visits the platform can be thought of *as good as random* with respect to prices, an assumption that has strong empirical support as shown in Figure 4.

Our instrument considers the number of prices a user *could have seen* had they visited the website at a different time but *did not see*. The instrument then effectively exploits these *unseen prices* by the user for the same product in nearby time periods. The intuition is simple: while a purchase decision is driven by the prices exposed to, it does not depend on the "unseen prices." However, price changes are often clustered in nearby hours or days, hence it is a strong instrument for the actual exposure PVS_{it}. Recall that the data covers the time series of prices, including those when the user is not browsing a particular product; and unseen prices can only influence the outcome through the prices she did see. To make things concrete, consider two users i and i' who both visited the retailer's website thrice in the past 30 days, albeit on different days or at different times on the same day. For simplicity, assume that i and i' browsed the same product j. During the past 30 days, j's price fluctuated independently of these two users' visits. And because their visitation timings vary, user i was exposed to a single price, whereas user i' was exposed to three price changes. The purchase decision that both users make today depends upon their respective PVS_{it} and $PVS_{i't}$. However, it does not depend upon the prices not observed, which makes the unseen price variability a valid instrument.

Table 3: Exposure to higher price variability increases price sensitivity: Two Stage Control Function estimates

Dependent Variable:	Units
Model:	(1)
Variables	
Log price	-1.26***
	(0.061)
Log price x Log price variability stock	-0.088***
	(0.008)
Log price variability stock	0.912***
	(0.023)
Log # of prior purchases	-0.527***
	(0.010)
Log # of visits	-0.139***
	(0.015)
Log # of products viewed	0.158***
	(0.005)
First stage residual - 1	-1.04***
	(0.025)
First stage residual - 2	0.077***
	(0.010)
Fixed-effects	
User	✓
Product	✓
Year week	✓
Day of week	✓
Hour	✓
Fit statistics	
First stage F-stat - 1	147.4***
First stage F-stat - 2	130.3***
Observations	21,194,749
Pseudo R^2	0.243
Log-Likelihood	-4,375,839.9

*The table reports Control Functions estimates for Model 2. Each observation is at the user-product-visit level and the dependent variable is the number of units of the product purchased by the user. The PVS is instrumented using the number of "unseen prices". The interaction between PVS is instrumented using the interaction between the number of "unseen prices" and price. First stage F-stats are reported in the bottom part of the table and they indicate that the instruments are fairly strong. Additionally, conditional F-stat testing for weak instruments jointly also shows that the instruments are strong (Cond. F-stat 1: 4045.3, Cond. F-stat 2: 3228.7). The first row is the baseline price sensitivity and the second row shows the coefficient of interest, i.e., the interaction between (log) price and the (log) PVS. Bootstrapped and Clustered (User & Product) standard errors are shown in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

We use the "unseen prices" instrument described above to causally pin down the effect of price variability on price sensitivity. We use a two-stage control function (Petrin and Train, 2010; Ebbes et al., 2021) approach because Model 2 is non-linear. We instrument for

the price variability stock (PVS_{it}) and its interaction with price ($\log(P_{ijt}) \times PVS_{it}$). In the first stage, we run two regressions: (a) PVS_{it} on the instrument Z_{it}, exogenous controls (X_{ijt}), and the fixed effects from Model 2, and (b) $\log(P_{ijt}) \times PVS_{it}$ on $\log(P_{ijt}) \times Z_{it}$, X_{ijt}, and the fixed effects. In the second stage, we estimate Model 2 by including the residuals from the two first-stage models.[6] Standard errors are bootstrapped and clustered at the user and product level.

Table 3 presents the results from the control function. Once again, price variability exacerbates price sensitivity. We find a negative and significant coefficient for the interaction between price and price variability when the PVS is instrumented using unseen price changes. These results provide direct evidence that consumers become more price sensitive when exposed to algorithmic pricing-induced price variability.

5 Heterogeneous Effects to Price Variability

Next, we examine factors that amplify or attenuate the impact of Price Variability Stock (PVS) on consumer price sensitivity. Understanding this heterogeneity helps clarify the behavioral mechanisms underlying our main results and sheds light on more nuanced managerial and welfare implications of algorithmic pricing. We report the following empirical analyses.

- **Customer segments**. We explore heterogeneity across customer characteristics. In particular, we examine two dimensions. First, we segment users based on the time of day in which they typically shop, namely"morning shoppers," "daytime shoppers," and "night shoppers." The results, reported in Appendix G.1, show that consumers in all segments become more price sensitive when exposed to greater algorithmic price variability. However, the effect is strongest among night shoppers. One possible explanation is that these consumers may face fewer time constraints or distractions while browsing, allowing them to pay closer attention to prices.

  Second, we classify users according to whether their delivery zip code corresponds to a low-income or high-income area using U.S. Census microdata.[7] The results, shown in Appendix G.2, reveal that the increase in price sensitivity induced by price variability is significantly stronger for consumers located in lower-income areas.

[6]The control function is equivalent to running a 2SLS procedure for instrumental variables when the model is linear. Recall that the 2SLS replaces the observed endogenous variable with the predicted values from the first-stage regression.

[7]https://www.census.gov/data/developers/data-sets/acs-5year.html.

This pattern is consistent with prior evidence that financially constrained households have lower search costs, and hence may monitor (and respond to) prices more closely (Mehta et al., 2003; Aguiar and Hurst, 2007). These findings highlight potential welfare implications of algorithmic pricing: if price variability disproportionately increases price sensitivity among lower-income consumers, AI adoption for pricing may affect consumer surplus and distributional outcomes across socioeconomic groups.

- **Product type**. We also examine whether the effect of PVS varies across product categories. In particular, we compare perishable and non-perishable products. We find that the increase in price sensitivity induced by price variability is significantly stronger for non-perishable products. This result is consistent with the notion that such products can be stockpiled, allowing consumers to strategically time purchases in response to observed price fluctuations (Hendel and Nevo, 2004). When prices change frequently, consumers may become more attentive to price movements and delay purchases until favorable prices appear. The results are reported in Appendix G.3.

- **Awareness of price variability**. A natural question is whether consumers are actually aware of their exposure to price variability—that is, whether they notice that prices change frequently. To shed light on this mechanism, we examine two settings in which price changes are more likely to be salient to consumers. We find that the effect of PVS on price sensitivity is amplified when (a) underlying price dispersion is larger (i.e., when price changes occur in larger absolute magnitudes) and (b) when prices deviate from consumer's previously paid price. Both patterns are consistent with increased awareness of price fluctuations: large price movements (Gunadi and Evangelidis, 2022) and deviations from anchor prices (Mazumdar et al., 2005), respectively, are more likely to capture consumers' attention and trigger stronger behavioral responses. These results therefore support the interpretation that consumers notice algorithmic price variability and become more price sensitive accordingly. The results are reported in Appendix G.4.

6 Online Lab Experiment

Our previous analyses in collaboration with an online grocery platform indicate that exposure to high price variability exacerbates consumers' price sensitivity. We complement

this field evidence with a pre-registered incentive-compatible online experiment to further generalize our findings.

6.1 Experiment Design

We recruit 700 participants from Prolific (self-reported average age of 38 and 45% female, 52 failed an attention check question). Participants are asked to indicate how many units of a single product (e.g., Nutella) they would buy in each of 12 sequential periods. They receive a budget to spend across periods and the price might fluctuate from period to period. Critically, their bonus payout depended on the total units purchased and savings accrued, rewarding real-world behavior of buying more at lower prices.[8]

Participants are randomly assigned to one of two treatment conditions: (1) algorithmic prices (High-PV) and (2) non-algorithmic prices (Low-PV). Price series are simulated based on real data, and therefore the price variation resembles what online platforms do with respect to algorithmic prices. As a result, algorithmic prices fluctuate frequently, whereas non-algorithmic prices are fairly stationary with small infrequent jumps. The prices across conditions have the same average price (but different price variability). Reassuringly, we find similar results in a robustness experiment done with MBA students (Appendix H).

6.2 Price Sensitivity

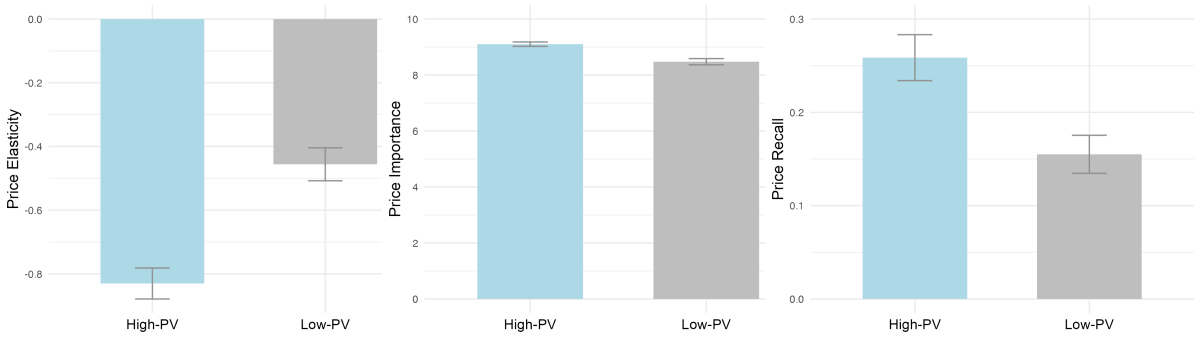
We pool at the data at the participant $\times$ period level, and then estimate the following model to test whether algorithmic pricing exacerbates price sensitivity:

$$\log(Y_{it}) = \beta_0 + \beta_1 \log(P_{it}) + \epsilon_{it} \tag{3}$$

where Y_{it} and P_{it} denote the quantity purchased by participant i in period t and price in period t, respectively; and the model is estimated separately for participants exposed to High-PV and Low-PV. Our object of interest is β_1, which captures the coefficient of price elasticity. We report the price coefficients in Figure 8a (bars are standard errors). Consistent with our results from the field, participants exposed to a relatively higher price variability experience a larger price sensitivity when simulating purchase decisions. In

[8] To the best of the authors' knowledge, there are no studies that have explored algorithmic pricing and price sensitivity in a controlled experiment. This incentive-compatible setting might be useful for scholars in the field interested in testing other dimensions of algorithmic pricing.

particular, $\hat{\beta}_{1,\text{High-PV}} = -0.83$ (95%CI $= [-0.93, -0.73]$) and $\hat{\beta}_{1,\text{Low-PV}} = -0.46$ (95%CI $= [-0.56, -0.35]$).



(a) Price elasticity (b) Price importance (c) Price recall

Figure 7: Algorithmic pricing and price salience

6.3 Price Salience

Next, we shed light on the underlying behavioral mechanism. As we motivate through a theoretical illustration in Appendix I (and discussed in the Introduction), the effect of algorithmic pricing on price elasticity is theoretically ambiguous. However, our evidence in Section G indicates that exposure to the effects of algorithmic pricing are amplified by large price changes as well as by deviations from anchor prices. Consistent with this idea, we posit that algorithmic pricing may plausibly drive attention to prices and such salience heightens price sensitivity.[9]

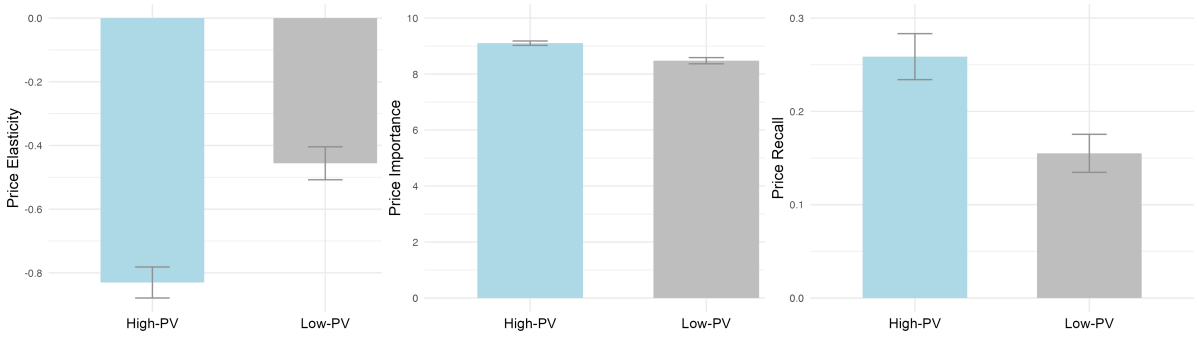
After completing the 12-period shopping trip, we ask participants to rate (0–10 scale) the importance of price in their decisions. This measure of price salience aligns with prior studies that operationalize price salience as the extent to which consumers assign weight to prices in their decision-making process (Wathieu et al., 2004; Lalwani and Forcum, 2016; Sheehan and Van Ittersum, 2018). Thus, a higher score indicates greater importance and hence heightened attention to prices.

The results are summarized in Figure 8b. A Welch's two-sample t-test revealed a significant difference in means for price importance between the algorithmic pricing ($M_{\text{High-PV}} = 9.10$) and non-algorithmic pricing ($M_{\text{Low-PV}} = 8.48$) conditions (t(568.42) = 4.62, p = 0.001, 95% CI [0.36, 0.89]). Furthermore, a mediation analysis using Model 4 (Hayes, 2017) with

[9]While the following analyses focus on the role of price salience, we note that it does not preclude the existence of other interesting behavioral phenomena.

5,000 bootstrap samples shows that the relationship between participant-level price elasticity (in absolute value) and the price variability condition operates via price importance. Indeed, there is a significant indirect effect of the pricing condition on participants' price elasticity through price importance (b = 0.15, SE = 0.06, p = 0.017, 95%CI [0.33, 0.31]). Additional details are discussed in the Online Appendix H.

An alternative way to operationalize price salience is price recall (Alba and Chattopadhyay, 1986; Finkelstein, 2009). To illustrate, Alba and Chattopadhyay (1986) write: "*[...] exposure to a brand increases its salience, thereby increasing the ability of a consumer to recall it. [...] Not surprisingly, marketing variables that enhance the salience of a brand, such as advertising and usage, have been shown to be related directly to recall.*" Thus, after the question on price importance, participants are shown a brief visual stimulus comprising images of the focal product (e.g., Nutella) alongside a new item (e.g., Oreos). The screen, which includes product images, descriptions, and prices, vanishes after 5 seconds.



(a) Price elasticity (b) Price importance (c) Price recall

Figure 8: Algorithmic pricing and price salience

We then ask participants to recall the price of the new product. If price variability heightens price salience, then we expect a larger share of consumers in the High-PV treatment condition to better recall the price of Oreos. This strategic design is motivated by principles of visual cognition and uses salience of specific stimuli to enhance it. Placing just one Oreos product among other products is intentional—it drives attention naturally (bottom-up) and also aligns with what participants instinctively already recognize (top-down), thereby creating a strategic synergy that maximizes the perceptual impact of the stimulus (Kersten et al., 2004; Shelton and Scullin, 2017). Bottom-up processes, initiated by sensory features such as visual distinctiveness, operate involuntarily to capture attention swiftly. Simultaneously, top-down processes, shaped by cognitive expectations and prior knowledge, guide attention purposefully. This dual approach in our case maximizes

the likelihood of participants not only noticing but also actively processing and retaining the price details, offering a more nuanced evaluation of price variability on price recall.

Once again, algorithmic pricing makes price more salient. A visual summary is depicted in Figure 8c. Specifically, the proportion of correct responses is higher in the High-PV condition compared to the Low-PV condition. A Welch's two-sample t-test reveals a significant difference in means for the share of correct price recall between High-PV ($M_{\text{High-PV}} = 0.259$) and Low-PV ($M_{\text{Low-PV}} = 0.155$) conditions ($t(610.1) = 3.24$, $p = 0.001$, 95% CI [0.04,0.17]). Moreover, a two-sample proportions test shows that the difference is statistically significant ($\chi^2 = 9.73$, $p = 0.002$). In the Appendix H, we report similar results when measuring price recall within 10 cents. In the Appendix J, eye-tracking field data shows that prices tend to drive attention—as measured by time spent looking at the screen—further supporting the link between prices and salience.

Collectively, the findings from the lab support our field evidence, i.e., exposure to high price variability exacerbates price sensitivity. We also find suggestive evidence that algorithmic pricing increases price salience (attention to prices), thereby heightening price sensitivity.

7 Robustness Checks

We implement several robustness checks for our main specification described in Model 2 as well as for the online lab experiments. Overall, the pattern of results is unchanged.

1. **Alternative specifications and functional forms.** We re-estimate Model 1 with more stringent controls, such as the interaction of price with search intensity and pentiles of continuous controls as dummy variables. We also estimate Model 2 using OLS and 2SLS. The results are shown in Appendix B.

2. **Alternative time windows.** We re-compute the PVS and time-varying controls by varying the rolling window to 15 days and 60 days. The results are shown in Appendix C.

3. **Alternative fixed effects.** We re-estimate our main Model 1 including state-month fixed effects as well as number of visits fixed effects. The results are shown in Appendix D.

4. **Alternative measure of PVS.** We redefine our measure of PVS. Instead of exposure to the number of distinct prices per product, we consider the number of price

changes per product. Analogously, for the instrument, we use the number of price changes the user could have seen but did not see for estimating the Two Stage Control Function model. The results, shown in Appendix E, are similar.

5. **Alternative instruments.** We use two alternative instruments for further robustness. We report these results in Tables F9 and F10. We observe similar findings.

   (a) *Other Markets.* This instrument exploits the fact that online grocers have the ability to price-discriminate across states (Aparicio et al., 2023). In our case, as part of their experimentation in price algorithms, the platform varied prices for the same product across states. Therefore, we instrument for PVS_{it} using the PVS that user i *would have experienced in another state* holding constant the same visitation timestamps. The validity of this IV relies on (a) that prices in another state are exogenous to a user—similar in spirit to Hausman-style instruments (Hausman, 1996; Berry and Haile, 2014)—and (b) prices or price changes are correlated across markets (DellaVigna and Gentzkow, 2019).

   (b) *Other Products.* Another instrument builds on the evidence that retailers often synchronize price changes across products from the same category or brand at close time intervals (Anderson et al., 2015). For instance, all flavors of the same yogurt brand experience price updates together. Therefore, we instrument PVS_{it} using the number of price changes, in the same visitation periods, of *random* products in the same category which the user *did not see*. For each product j that user i browsed at time t, we draw a random unseen product j' in the same category of product j at time t and utilize j' to compute the instrument stock.[10] As before, price variability of similar products is a strong instrument because (a) price changes are correlated but (b) price variability in unseen products is uncorrelated to a purchase decision (Ellison and Ellison, 2009).

6. **Robustness for lab experiments.** We report several robustness checks in the Online Appendix H for our online lab experiment results described in Section 6.2. They include an interacted specification between price and the treatment indicator (High-PV), estimates from a Quasi-Poisson model, estimates from a mixed-effects model, and a similar experiment with MBA students from a large European university.

[10] The instrument is similar to the IV approach in Assad et al. (2023)'s study of algorithmic pricing and collusion across gas stations.

8 Discussion

Artificial Intelligence automates decisions that were historically made by humans. Algorithmic pricing, a prominent application of AI, enables firms to adjust prices dynamically for thousands of products using real-time data. As businesses increasingly adopt such systems, consumers are exposed to prices set and updated by machines rather than by human managers. A defining feature of these systems is the high frequency of price adjustments they generate. This raises an important question: how does exposure to algorithmic price variability influence consumer behavior? By combining field data and controlled experiments, our paper provides new evidence on the behavioral consequences of algorithmic pricing.

We study this question in collaboration with a large online grocery retailer in the United States that implemented algorithmic pricing on its platform. The resulting system generates (very) frequent price changes across thousands of products, consistent with objectives of price experimentation. Because grocery shopping involves repeated visits and purchases, consumers are differentially exposed to price variability for the same products over time. We exploit this variation to estimate how exposure to algorithmic pricing–induced price variability affects consumers' price sensitivity. To validate the behavioral mechanisms behind our field findings, we complement the analysis with an incentive-compatible, ore-registered online laboratory experiment.

Our results yield several empirical insights. First, we provide causal evidence that exposure to algorithmic pricing–induced price variability amplifies consumer price sensitivity. To our knowledge, this paper is among the first to document this unintended behavioral consequence of algorithmic pricing. Furthermore, we introduce a new way to conceptualize and measure exposure to algorithmic price variability. Our measure, Price Variability Stock (PVS), captures the cumulative number of distinct prices (or price changes) a user observes for a given product and provides an intuitive framework to quantify the intensity of exposure to price fluctuations. Finally, we find suggestive evidence of some underlying behavioral mechanisms. More specifically, frequent price changes draw consumers' attention to prices, which in turn increases their responsiveness to price differences. Moreover, the effects are amplified when price changes are greater and when they deviate from consumers' anchor prices.

Taken together, these findings have important managerial implications. Firms often implement algorithmic pricing systems with the expectation that optimization and experimentation will ultimately increase profitability. However, our results reveal a potential

"boomerang" effect: by repeatedly exposing consumers to fluctuating prices, algorithmic pricing may increase salience to price and make consumers more responsive to price changes. In this sense, the pricing system may inadvertently undermine its own objective. Prices that appear optimal based on historical demand estimates may no longer remain optimal once consumers' price sensitivity evolves in response to repeated exposure to price variability. As a result, this behavioral response eats some of the gains that algorithmic pricing aims to capture. In fact, fostering greater price sensitivity is likely undesirable for most firms—e.g., managers may have to more aggressively "discount products with the highest price elasticity" to make promotions attractive to consumers (Fantini and Narayandas, 2023).

Price Personalization. These price variability-driven behavioral responses also have implications for the emerging use of AI in price personalization and customized pricing strategies (Dubé and Misra, 2023). If exposure to price variability increases price sensitivity, firms may benefit from incorporating consumers' historical exposure to prices into their pricing algorithms. For example, firms could display prices that consumers have previously observed rather than introducing new optimized prices that increase perceived volatility. Similarly, firms may impose constraints on the magnitude or frequency of price changes to reduce the shock of variability. To illustrate, suppose an algorithm computes an optimal price of $3.17 for a product, but user A has previously seen the product priced at $3.09 and $3.99. Instead of displaying the newly optimized price, the firm may choose to display the previously observed price of $3.09 to user A while displaying $3.17 to user B. This approach effectively regularizes price changes and reduces the behavioral consequences of price volatility. More broadly, firms may benefit from incorporating penalties or constraints on the frequency of price changes when designing pricing algorithms.

Our findings also have implications for consumer welfare and market outcomes. The heterogeneous effects we document suggest that the increase in price sensitivity is stronger among consumers located in lower-income areas. From a pricing perspective, this behavioral response may generate distributional consequences. If algorithmic pricing systems learn that demand is more elastic for certain consumer segments, profit-maximizing pricing rules imply lower markups for those segments. Over time, this could translate into lower equilibrium prices in markets with more price-sensitive consumers, potentially benefiting lower-income households through higher consumer surplus. At the same time, this potential benefit may come with costs. Increased price variability may require consumers to devote greater attention and cognitive effort to monitoring prices and iden-

tifying favorable deals. Intuitively, consumers may need to spend more time and effort to find (or wait for) good deals. In this sense, algorithmic pricing may simultaneously lower prices while increasing the behavioral burden associated with price search. Future research should further examine welfare implications of algorithmic pricing.

From a policy perspective, these findings raise additional considerations. Because increased price sensitivity emerges as an unintended consequence of algorithmic pricing, our results highlight the importance of transparency in the deployment of such systems. Recently, the U.S. Federal Trade Commission has launched an investigation into so-called "surveillance pricing," where firms use consumer data and algorithms to tailor prices to individuals (FTC, 2025; New York Times, 2025). A growing literature has examined the supply-side implications of algorithmic pricing, including collusion risks, competitive strategy, and inventory optimization. Our work complements this literature by highlighting the relatively understudied demand-side consequences of algorithmic pricing systems.

Finally, our findings open several avenues for future research. First, it would be valuable to distinguish between short-run and long-run behavioral responses to algorithmic price variability. As algorithmic pricing technologies are still relatively new, both firms and consumers are continuously adapting to them. Second, competition introduces an important dimension that remains largely unexplored. Pricing algorithms often incorporate competitor prices as key inputs, and firms increasingly operate in markets where multiple players deploy algorithmic pricing simultaneously. If algorithmic pricing increases consumer price sensitivity, how might this affect competitive dynamics or the stability of algorithmic collusion? More broadly, understanding the equilibrium interactions between consumers who adapt behaviorally to pricing algorithms and firms that strategically deploy those algorithms represents an important direction for future research.

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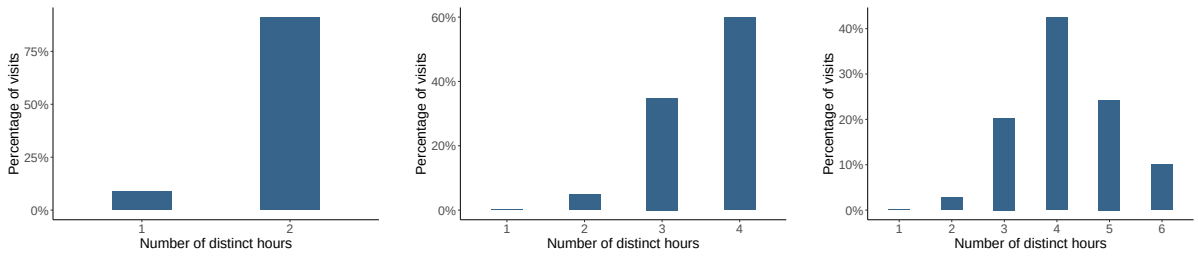
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Online Appendix

A User visitation patterns

Figure A1 documents the variation in the timing of a given user's visit to the platform. Panel A1a shows that among users who visited a given product twice during our sample period, 90% did so during two distinct hours of the day. Similarly, Panel A1c shows that among users who visited a given product six times during our sample period, more than 80% visited during 4 or more distinct hours of the day.



(a) First 2 visits for a given product

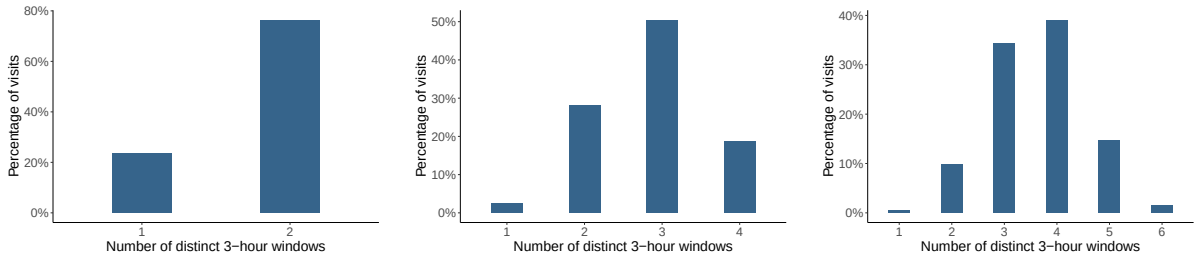
(b) First 4 visits for a given product

(c) First 6 visits for a given product

Figure A1: Number of distinct hours users visited on their across different days.

Figure A2 extends the observation window to 3-hour time blocks (e.g., 6 - 9 am, 9 am - 12 pm, and so on). Analogously. Panel A2a shows that among users who visit a given product twice in our sample, $\sim 80\%$ do so in two distinct 3-hour time windows. Similarly, Panel A2c shows that among users who visit a given product six times in our sample, $\sim 60\%$ visit in distinct 4 or more distinct 3-hour time windows.

Both these figures help illustrate the fact that user visitation patterns are "haphazard", which subsequently generates exposure to different prices for the same product over time.



(a) First 2 visits for a given product

(b) First 4 visits for a given product

(c) First 6 visits for a given product

Figure A2: Number of distinct 3-hour time windows users visited on their across different days.

B Robustness to alternate specifications and functional forms

Table B1 presents results using alternative specifications and controls as compared to our main specification (Table 2). Column (1) shows baseline price sensitivity after controlling for user, product, and year-week fixed effects. Column (2) includes the PVS and its interaction with (log) price. The second row shows the main coefficient of interest. A negative and significant coefficient implies that users become more price sensitive when exposed to higher price variability. We include day-of-week and hour-of-day fixed effects in Column (3); the results are unchanged. In Column (4) we add time-varying controls and the interaction of users' historical search intensity (measured using the number of products viewed in the past 30 days) with (log) price. Finally, in Column (5) we discretize the time-varying controls to include dummies for each quartile. Across all specifications, we find that the key result is robust.

Table B1: Estimates from Quasi-Poisson model using alternate specifications

Dependent Variable:			Units		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Log price	-1.30***	-1.27***	-1.27***	-1.25***	-1.27***
	(0.061)	(0.061)	(0.061)	(0.062)	(0.061)
Log price x Log price variability stock		-0.048***	-0.048***	-0.056***	-0.057***
		(0.006)	(0.006)	(0.008)	(0.006)
Log price variability stock		0.200***	0.200***	0.134***	0.146***
		(0.013)	(0.013)	(0.017)	(0.014)
Log # of prior purchases				-0.441***	
				(0.009)	
Log # of visits				0.183***	
				(0.013)	
Log # of products viewed				0.230***	
				(0.007)	
Log price × Log # of products viewed				-0.005**	
				(0.003)	
# of prior purchases - 2					-0.010
					(0.019)
# of prior purchases - 3					-0.211***
					(0.019)
# of prior purchases - 4					-0.979***
					(0.018)
# of visits - 2					0.950***
					(0.051)
# of visits - 3					1.09***
					(0.019)
# of visits - 4					1.29***
					(0.022)
# of products viewed - 2					-0.857***
					(0.049)
# of products viewed - 3					-0.385***
					(0.012)
Fixed-effects					
User	✓	✓	✓	✓	✓
Product	✓	✓	✓	✓	✓
Year week	✓	✓	✓	✓	✓
Day of week			✓	✓	✓
Hour			✓	✓	✓
Fit statistics					
Observations	21,194,749	21,194,749	21,194,749	21,194,749	21,194,749
Pseudo R^2	0.231	0.232	0.232	0.240	0.239
Log-Likelihood	-4,441,018.1	-4,438,786.6	-4,436,500.4	-4,389,810.2	-4,397,683.5

*The table reports Quasi-Poisson estimates of Model 2 with alternate specifications and controls. Each observation is at the user-product-visit level and the dependent variable is the number of units of the product purchased by the user. Columns (1) and (2) control for user, product, and year-week fixed effects. Columns (3), (4), and (5) additionally control for day-of-week and hour-of-day fixed effects. Column (4) includes the interaction of (log) price with the number of products a user viewed in the past 30 days. Column (5) more flexibly includes time-varying controls as quartile dummies. Clustered (User & Product) standard errors are shown in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table B2 reports OLS estimates of Model 2 with $\log(y_{ijt}+1)$ as the dependent variable. Both columns include user, product, and year-week fixed effects along with time-varying controls. In addition, Column (2) includes day-of-week and hour-of-day fixed effects to account for user visitation patterns. The second row in both columns shows the key coefficient of interest. Once again, using OLS models, our main results remain similar, i.e., users show an increase in price sensitivity with increased exposure to price variability.

Table B2: Estimates from OLS with fixed effects

Dependent Variable:	Log units	
Model:	(1)	(2)
Variables		
Log price	-0.043***	-0.043***
	(0.003)	(0.003)
Log price x Log price variability stock	-0.001***	-0.001***
	(0.0002)	(0.0002)
Log price variability stock	0.003***	0.003***
	(0.0005)	(0.0005)
Log # of prior purchases	-0.017***	-0.017***
	(0.0004)	(0.0004)
Log # of visits	0.004***	0.003***
	(0.0004)	(0.0004)
Log # of products viewed	0.006***	0.006***
	(0.0002)	(0.0002)
Fixed-effects		
User	✓	✓
Product	✓	✓
Year week	✓	✓
Day of week		✓
Hour		✓
Fit statistics		
Observations	21,194,749	21,194,749
Pseudo R^2	-0.258	-0.258
Log-Likelihood	6,689,185.5	6,689,982.4

The table reports OLS estimates of Model 2. Each observation is at the user-product-visit level and the dependent variable is the $\log+1$ *number of units of the product purchased by the user. Both columns show estimates from a fixed effects model with time-varying controls. Column (2) additionally controls for day-of-week and hour-of-day fixed effects. The first row is the baseline price sensitivity and the second row shows the coefficient of interest, i.e., the interaction between (log) price and (log) PVS. Clustered (User & Product) standard errors are shown in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table B3 replicates the Control Function estimates from Table 3 using 2SLS. Recall that the price variability stock (PVS) measures the number of unique prices a user sees for a given product over a specific time period. The measure is then aggregated across all products the user views to account for cross-product spillovers. As described in Section 4.1, we instrument PVS using the number of "unseen prices", i.e., the number of prices of the same product over the same time period that the user did not see. Subsequently, we estimate Model 2 using 2SLS where we instrument for PVS and its interaction with (log) price. The results, presented in Table B3, are similar, i.e., users become more price sensitive when exposed to higher price variability.

Table B3: Estimates from 2SLS model

Dependent Variable:	Log units
Model:	(1)
Variables	
Log price x Price variability stock	-0.003***
	(0.0003)
Log price	-0.043***
	(0.003)
Price variability stock	0.029***
	(0.0009)
Log # of prior purchases	-0.019***
	(0.0004)
Log # of visits	-0.007***
	(0.0005)
Log # of products viewed	0.004***
	(0.0002)
Fixed-effects	
User	✓
Product	✓
Year week	✓
Day of week	✓
Hour	✓
Fit statistics	
Observations	21,194,749
F-test	127.2

*The table reports 2SLS estimates for Model 2. Each observation is at the user-product-visit level and the dependent variable is the number of units of the product purchased by the user. The PVS is instrumented using the number of "unseen prices". The interaction between PVS is instrumented using the interaction between the number of "unseen prices" and price. First stage F-stats are reported in the bottom part of the table and they indicate that the instruments are fairly strong. The first row is the baseline price sensitivity and the second row shows the coefficient of interest, i.e., the interaction between (log) price and (log) PVS. Bootstrapped and Clustered (User & Product) standard errors are shown in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

C Robustness to alternate time windows

Table C4 estimates Model 2 with alternate rolling windows to compute PVS and the corresponding time-varying covariates. Specifically, Column (1) considers a 15-day rolling window, and Column (2) considers a 60-day rolling window. The models are estimated using a Quasi-Poisson Likelihood and the results are similar to our main specification which uses a 30-day rolling window.

Table C4: Estimates from Quasi-Poisson model with alternate rolling windows

Dependent Variable:	Units	
Model:	(1)	(2)
Time window (days):	15	60
Variables		
Log price	-1.27***	-1.26***
	(0.061)	(0.061)
Log price x Log price variability stock	-0.074***	-0.036***
	(0.009)	(0.005)
Log price variability stock	0.195***	0.105***
	(0.020)	(0.012)
Log # of prior purchases	-0.426***	-0.424***
	(0.010)	(0.010)
Log # of visits	0.127***	0.127***
	(0.014)	(0.014)
Log # of products viewed	0.203***	0.205***
	(0.005)	(0.005)
Fixed-effects		
User	✓	✓
Product	✓	✓
Year week	✓	✓
Day of week	✓	✓
Hour	✓	✓
Fit statistics		
Observations	21,194,749	21,194,749
Pseudo R^2	0.239	0.239
Log-Likelihood	-4,394,502.7	-4,394,606.7

*The table reports Quasi-Poisson estimates of Model 2. Each observation is at the user-product-visit level and the dependent variable is the number of units of the product purchased by the user. Both columns show estimates from a fixed effects model with time-varying controls. Column (1) computes PVS and the corresponding time-varying covariates over a 15-day time window and Column (2) does it for a 60-day time window. The first row is the baseline price sensitivity and the second row shows the coefficient of interest, i.e., the interaction between (log) price and (log) PVS. Clustered (User & Product) standard errors are shown in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

D Robustness to alternate fixed effects

We re-estimate our main Model 2 including state × month fixed effects. The estimates are similar and reported in Table D5.

Table D5: Estimates from Quasi-Poisson model with fixed effects

Dependent Variable:	Units	
Model:	FE State (1)	FE State Year-Month (2)
Variables		
Log price	-1.26***	-1.26***
	(0.061)	(0.061)
Log price x Log price variability stock	-0.065***	-0.065***
	(0.007)	(0.007)
Log # of prior purchases	-0.441***	-0.443***
	(0.009)	(0.009)
Log # of visits	0.183***	0.183***
	(0.013)	(0.013)
Log # of products viewed	0.219***	0.219***
	(0.005)	(0.005)
Log Price variability stock	0.151***	0.154***
	(0.015)	(0.015)
Fixed-effects		
User	✓	✓
Product	✓	✓
Year week	✓	✓
Day of week	✓	✓
Hour	✓	✓
State	✓	
State Year-Month		✓
Fit statistics		
Observations	21,194,749	21,194,749
Pseudo R^2	0.240	0.240
Log-Likelihood	-4,389,759.6	-4,389,117.4

Clustered (User & Product) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Additionally, we re-estimate our main model including $visits_{it}$ and $visits_{it}$ squared, as well as $visits_{it}$ fixed effects. The estimates are similar and reported in Table D6.

Table D6: Estimates from Quasi-Poisson model with fixed effects

Dependent Variable:	Units	
Model:	(1)	(2)
Variables		
Log price	-1.26***	-1.26***
	(0.061)	(0.061)
Log price x Log price variability stock	-0.062***	-0.061***
	(0.007)	(0.007)
Log # of prior purchases	-0.441***	-0.444***
	(0.009)	(0.009)
Visits	0.036***	
	(0.004)	
Visits square	-0.0003***	
	(7.21×10^{-5})	
Log # of products viewed	0.248***	0.277***
	(0.004)	(0.006)
Log Price variability stock	0.131***	0.115***
	(0.015)	(0.015)
Fixed-effects		
User	✓	✓
Product	✓	✓
Year week	✓	✓
Day of week	✓	✓
Hour	✓	✓
Visits		✓
Fit statistics		
Observations	21,194,749	21,194,749
Pseudo R^2	0.240	0.240
Log-Likelihood	-4,389,516.2	-4,388,121.4

Clustered (User & Product) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

E Robustness to alternate measures of price variability stock

In our main specification, we measure exposure to price variability using the number of unique prices a user is exposed to for a given product. As robustness, we use an alternate measure of PVS: the number of price changes. Specifically, for each user-product combination during the relevant time window (30 days), we tabulate the number of price changes the user was exposed to. We then aggregate this number across all products a user sees within that time period to compute the user's price variability stock.

Table E7 reports the estimates using this alternate measure. The first row shows the baseline price sensitivity and the second row shows the coefficient of interest. Again, we see an increase in price sensitivity due to exposure to increased price variability.

Table E7: Estimates from Quasi-Poisson model with fixed effects: PVS using price changes

Dependent Variable:	Units	
Model:	(1)	(2)
Variables		
Log price	-1.26***	-1.26***
	(0.061)	(0.061)
Log price x Log price variability stock (price changes)	-0.061***	-0.061***
	(0.007)	(0.007)
Log price variability stock (price changes)	0.152***	0.154***
	(0.015)	(0.015)
Log # of prior purchases	-0.444***	-0.441***
	(0.009)	(0.009)
Log # of visits	0.180***	0.179***
	(0.013)	(0.013)
Log # of products viewed	0.221***	0.219***
	(0.005)	(0.005)
Fixed-effects		
User	✓	✓
Product	✓	✓
Year week	✓	✓
Day of week		✓
Hour		✓
Fit statistics		
Observations	21,194,749	21,194,749
Pseudo R^2	0.240	0.240
Log-Likelihood	-4,391,154.9	-4,389,801.6

*The table reports Quasi-Poisson estimates of Model 2. Each observation is at the user-product-visit level and the dependent variable is the number of units of the product purchased by the user. Both columns show estimates from a fixed effects model with time-varying controls. Column (2) additionally controls for day-of-week and hour-of-day fixed effects. The first row is the baseline price sensitivity and the second row shows the coefficient of interest, i.e., the interaction between (log) price and (log) PVS. Clustered (User & Product) standard errors are shown in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table E8 is the analog of the main Control Function estimates Table (3) with the PVS computed using the number of price changes instead of the number of unique prices.

Correspondingly, PVS is then instrumented using the number of "unseen price changes" computed for the same product over the same time period. Standard Errors are computed using cluster bootstrap at the user and product level. Results are again consistent; users when exposed to higher price variability exhibit a higher degree of price sensitivity.

Table E8: Estimates from Two Stage Control Function: instrument using the number of unseen price changes

Dependent Variable:	Units
Model:	(1)
Variables	
Log price	-1.29***
	(0.062)
Log price x Log price variability stock (price changes)	-0.064***
	(0.009)
Log price variability stock (price changes)	1.49***
	(0.029)
Log # of prior purchases	-0.602***
	(0.011)
Log # of visits	-0.467***
	(0.017)
Log # of products viewed	0.103***
	(0.005)
First stage residual - 1	-1.44***
	(0.029)
First stage residual - 2	0.005
	(0.009)
Fixed-effects	
User	✓
Product	✓
Year week	✓
Day of week	✓
Hour	✓
Fit statistics	
First stage F-stat - 1	125.4***
First stage F-stat - 2	106.3***
Observations	21,194,749
Pseudo R^2	0.243
Log-Likelihood	-4,371,740.8

*The table reports Control Functions estimates for Model 2. Each observation is at the user-product-visit level and the dependent variable is the number of units of the product purchased by the user. The PVS is instrumented using the number of "unseen price changes". The interaction between PVS is instrumented using the interaction between the number of "unseen price changes" and price. First stage F-stats are reported in the bottom part of the table and they indicate that the instruments are fairly strong. The first row is the baseline price sensitivity and the second row shows the coefficient of interest, i.e., the interaction between (log) price and (log) PVS. Bootstrapped and Clustered (User & Product) standard errors are shown in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

F Robustness to alternate instrumental variables

In addition to the instrument used in our main specification, we use two additional instruments to verify the robustness of our findings. Specifically, we instrument the PVS, measured using the number of unique prices for a given product over a pre-specified time period, using: (a) the prices for the same product in different markets, and (b) the prices for other products in the same category.

Results using the Control Function approach and 2SLS are shown in Tables F9 and F10 respectively. We find consistent results across all three instruments. First stage results for all three instruments are shown in Table F11.

Table F9: Estimates from Two State Control Function using alternative instruments

Dependent Variable:	Units	
	State	Category
Model:	(1)	(2)
Variables		
Log price	-1.39***	-0.994***
	(0.068)	(0.061)
Log price x Log price variability stock	-0.045***	-0.036***
	(0.006)	(0.008)
Log price variability stock	0.332***	0.642***
	(0.018)	(0.020)
Log # of prior purchases	-0.495***	-0.628***
	(0.016)	(0.022)
Log # of visits	0.158***	0.116***
	(0.026)	(0.019)
Log # of products viewed	0.130***	0.070***
	(0.009)	(0.007)
First stage residual - 1	-0.465**	-1.07***
	(0.217)	(0.116)
First stage residual - 2	0.284***	0.229***
	(0.093)	(0.048)
Fixed-effects		
User	✓	✓
Product	✓	✓
Year week	✓	✓
Day of week	✓	✓
Hour	✓	✓
Fit statistics		
Observations	6,805,643	5,659,955
Pseudo R^2	0.277	0.376
Log-Likelihood	-1,331,885.9	-1,257,678.2

*The table reports Control Functions estimates for Model 2 estimated using two additional instruments – 1) prices for the same product in a different state, and 2) prices for other products from the same category. Each observation is at the user-product-visit level and the dependent variable is the number of units of the product purchased by the user. The first row is the baseline price sensitivity and the second row shows the coefficient of interest, i.e., the interaction between (log) price and (log) PVS. Bootstrapped and Clustered (User & Product) standard errors are shown in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table F10: Estimates from 2SLS using alternative instrumental variables

Dependent Variable:	Log units	
	State	Category
Model:	(1)	(2)
Variables		
Log price	-0.038***	-0.036***
	(0.002)	(0.004)
Log price x Log price variability stock	-0.001***	-0.002***
	(0.0002)	(0.0004)
Log price variability stock	0.009***	0.035***
	(0.0005)	(0.001)
Log # of prior purchases	-0.018***	-0.045***
	(0.0006)	(0.001)
Log # of visits	0.002***	0.023***
	(0.0007)	(0.0007)
Log # of products viewed	0.003***	-0.041***
	(0.0003)	(0.001)
Fixed-effects		
User	✓	✓
Product	✓	✓
Year week	✓	✓
Day of week	✓	✓
Hour	✓	✓
Fit statistics		
Observations	6,805,643	5,659,955

The table reports 2SLS estimates for Model 2 estimated using two additional instruments – 1) prices for the same product in a different state, and 2) prices for other products from the same category. Each observation is at the user-product-visit level and the dependent variable is the $\log +1$ *number of units of the product purchased by the user. The first row is the baseline price sensitivity and the second row shows the coefficient of interest, i.e., the interaction between (log) price and (log) PVS. Clustered (User & Product) standard errors are shown in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table F11 shows the first stage results for all three instruments – 1) *unseen prices*, 2) prices in another *state*, and 3) prices for other products in the same *category*.

Table F11: First stage results for control function regression

Dependent Variables:	Log PVS	Log price x Log PVS	Log PVS	Log price x Log PVS	Log PVS	Log price x Log PVS
		Unseen prices		State		Category
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Log price	0.042***	-0.0005	0.003***	0.013***	0.001	-0.005
	(0.004)	(0.011)	(0.0007)	(0.002)	(0.0009)	(0.003)
IV	0.290***	-0.283***	0.995***	-0.009***	0.951***	-0.025***
	(0.003)	(0.009)	(0.0005)	(0.0010)	(0.002)	(0.004)
IV interaction	-0.007***	0.403***	-0.0006***	0.997***	0.003***	0.969***
	(0.0009)	(0.004)	(0.0001)	(0.0004)	(0.0005)	(0.002)
Log # of prior purchases	0.107***	0.219***	0.0009	0.002	0.0005	0.002
	(0.003)	(0.007)	(0.0006)	(0.001)	(0.0009)	(0.002)
Log # of visits	0.318***	0.653***	0.004***	0.008***	-0.015***	-0.033***
	(0.008)	(0.018)	(0.001)	(0.003)	(0.001)	(0.003)
Log # of products viewed	-0.033***	-0.059***	0.0010**	0.002***	0.009***	0.019***
	(0.002)	(0.005)	(0.0004)	(0.0009)	(0.0004)	(0.0010)
Fixed-effects						
User	✓	✓	✓	✓	✓	✓
Product	✓	✓	✓	✓	✓	✓
Year week	✓	✓	✓	✓	✓	✓
Day of week	✓	✓	✓	✓	✓	✓
Hour	✓	✓	✓	✓	✓	✓
Fit statistics						
Observations	21,194,749	21,194,749	6,805,643	6,805,643	5,659,955	5,659,955
F-test	147.4	130.3	31,992.0	31,572.9	3,046.6	2,988.0

Clustered (User & Product) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

G Heterogeneous Effects

G.1 User segments: shopping time

Table G12 shows estimates from our main specification split across users' shopping time preferences. More specifically, we classify users based on the time they visit the online retailer's website into three categories: (a) morning shoppers (more than 50% of total visits are between 6 am - 12 pm), (b) day shoppers (more than 50% of total visits are between 12 pm - 6 pm), and (c) night shoppers (remaining users). Subsequently, we re-estimate the main specification of Model 2 separately for each of these users with a Quasi-Poisson likelihood. Given a latent concern about users' visit timings confounding our findings, this classification allows us to check the stability of our results across users with different shopping time preferences. Our results are consistent for all three user segments, with stronger effects among night shoppers.

Table G12: User segments: morning, day, and night shoppers

Dependent Variable:	Units		
	Morning Shoppers	Day Shoppers	Night Shoppers
Model:	(1)	(2)	(3)
Variables			
Log price	-1.19***	-1.26***	-1.33***
	(0.066)	(0.060)	(0.069)
Log price x Log price variability stock	-0.041***	-0.064***	-0.080***
	(0.011)	(0.012)	(0.008)
Log price variability stock	0.119***	0.164***	0.179***
	(0.025)	(0.028)	(0.018)
Log # of prior purchases	-0.396***	-0.504***	-0.446***
	(0.016)	(0.017)	(0.012)
Log # of visits	0.192***	0.212***	0.199***
	(0.022)	(0.024)	(0.018)
Log # of products viewed	0.194***	0.229***	0.204***
	(0.008)	(0.008)	(0.006)
Fixed-effects			
User	✓	✓	✓
Product	✓	✓	✓
Year week	✓	✓	✓
Day of week	✓	✓	✓
Hour	✓	✓	✓
Fit statistics			
Observations	6,813,469	5,778,325	8,602,955
Pseudo R^2	0.250	0.257	0.226
Log-Likelihood	-1,543,984.3	-1,202,854.2	-1,618,847.8

*The table reports Quasi-Poisson estimates of Model 2 for three user segments – 1) morning shoppers, 2) day shoppers, and 3) night shoppers. Users are classified into one of these three segments based on the time windows of the majority of their visits to the retailer's website. For all the columns, observations are at the user-product-visit level and the dependent variable is the number of units of the product purchased by the user. All columns show estimates from a fixed effects model with time-varying controls. The first row is the baseline price sensitivity and the second row shows the coefficient of interest, i.e., the interaction between (log) price and (log) PVS. Clustered (User & Product) standard errors are shown in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

G.2 User segments: high vs. low income

We also examine the stability of our results across user segments split by income. We use the American Community Survey 5-year data from 2018 to first classify zip codes in the US into either a low-income zip code or a high-income zip code based on a median split across the median household income dimension. Our data records the delivery zip code for each user and we use this information to map each user to either a low-income or high-income zip code. Subsequently, we re-estimate our main specification from Model 2 for these user segments separately.

The results are shown in Table G13. Column (1) shows the estimates for users from low-income zip codes and Column (2) shows it for high-income zip codes. It is worth noting that the baseline price sensitivity is significantly higher for users from low-income zip codes compared to users from high-income zip codes. Further, both user segments become more price sensitive when exposed to higher price variability, with stronger effects for low-income zip codes.

Table G13: User segments: low-income and high-income consumers

Dependent Variable:	Units	
	Low income zip codes	High income zip codes
Model:	(1)	(2)
Variables		
Log price	-1.49***	-1.21***
	(0.066)	(0.062)
Log price x Log price variability stock	-0.078***	-0.063***
	(0.012)	(0.007)
Log price variability stock	0.168***	0.153***
	(0.028)	(0.016)
Log # of prior purchases	-0.531***	-0.432***
	(0.022)	(0.011)
Log # of visits	0.240***	0.171***
	(0.029)	(0.014)
Log # of products viewed	0.234***	0.219***
	(0.010)	(0.005)
Fixed-effects		
User	✓	✓
Product	✓	✓
Year week	✓	✓
Day of week	✓	✓
Hour	✓	✓
Fit statistics		
Observations	4,398,816	16,516,463
Pseudo R^2	0.275	0.240
Log-Likelihood	-768,346.2	-3,518,121.9

*The table reports Quasi-Poisson estimates of Model 2 for users based on their zip codes. Users are classified into low-income or high-income zip codes based on their primary delivery zip code and the ACS 5-year data. For both columns, observations are at the user-product-visit level and the dependent variable is the number of units of the product purchased by the user. Both columns show estimates from a fixed effects model with time-varying controls. The first row is the baseline price sensitivity and the second row shows the coefficient of interest, i.e., the interaction between (log) price and (log) PVS. Clustered (User & Product) standard errors are shown in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

G.3 Product type

We also examine heterogeneity across product types. In particular, we separate our analysis between perishable items and non-perishable items. The product categories included as perishables are: Fresh Bakery Bread, Fresh Juice & Fruit Drinks, Beef, Chicken, Meat Substitutes, Vegetables, Yogurt, Turkey, Fruit, Fresh Produce, Dairy & Eggs, and Meat & Seafood.

Table G14 reports estimates. Once again, we observe consistent findings, with stronger effects on price sensitivity for non-perishable items.

Table G14: Product type: perishable and non-perishable products

Dependent Variable:	Units	
	Perishable	Non-perishable
Model:	(1)	(2)
Variables		
Log price	-1.17***	-1.31***
	(0.072)	(0.070)
Log price x Log price variability stock	-0.039***	-0.055***
	(0.015)	(0.008)
Log # of prior purchases	-0.342***	-0.452***
	(0.019)	(0.010)
Log # of visits	0.154***	0.190***
	(0.033)	(0.013)
Log # of products viewed	0.165***	0.223***
	(0.012)	(0.005)
Log Price variability stock	0.112***	0.133***
	(0.027)	(0.017)
Fixed-effects		
User	✓	✓
Product	✓	✓
Year week	✓	✓
Day of week	✓	✓
Hour	✓	✓
Fit statistics		
Observations	1,222,029	19,972,720
Pseudo R^2	0.285	0.246
Log-Likelihood	-297,092.1	-4,041,017.1

Clustered (User & Product) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

G.4 Price dispersion in price changes

To examine the role of the price dispersion underlying the PVS, we focus on user-product observations which are visited at least twice. Then, starting from the corresponding second visit, we compute the standard deviation of all price differences from one period to the next for each user–product in the relevant time window.

Table G15 reports estimates when we split the sample into high and low price dispersion of price changes. Notably, the effects are stronger when the underlying price changes are more dispersed.

Table G15: Price dispersion: low SD and high SD

Dependent Variable:	Units	
	Low SD	High SD
Model:	(1)	(2)
Variables		
Log price	-1.24***	-1.02***
	(0.074)	(0.063)
Log price x Log price variability stock	-0.054***	-0.076***
	(0.012)	(0.009)
Log # of prior purchases	-0.374***	-0.190***
	(0.014)	(0.011)
Log # of visits	0.456***	0.144***
	(0.021)	(0.018)
Log # of products viewed	0.067***	0.078***
	(0.007)	(0.007)
Log Price variability stock	0.023	0.045**
	(0.027)	(0.021)
Fixed-effects		
User	✓	✓
Product	✓	✓
Year week	✓	✓
Day of week	✓	✓
Hour	✓	✓
Fit statistics		
Observations	2,288,209	2,288,209
Pseudo R^2	0.344	0.249
Log-Likelihood	-726,740.9	-688,277.8

Clustered (User & Product) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Additionally, Table G16 repeats the analysis when we split the sample into quartiles of price dispersion of price changes.

Table G16: Price dispersion: SD 0–25% , SD 25–50%, SD 50–75%, & SD 75–100%

Dependent Variable:	Units			
	SD 0–25%	SD 25–50%	SD 50–75%	SD 75–100%
Model:	(1)	(2)	(3)	(4)
Variables				
Log price	-1.21***	-1.25***	-1.08***	-0.980***
	(0.082)	(0.087)	(0.067)	(0.077)
Log price x Log price variability stock	-0.046**	-0.053***	-0.074***	-0.076***
	(0.019)	(0.013)	(0.012)	(0.011)
Log # of prior purchases	-0.491***	-0.291***	-0.210***	-0.176***
	(0.021)	(0.015)	(0.013)	(0.016)
Log # of visits	0.719***	0.262***	0.174***	0.116***
	(0.033)	(0.023)	(0.023)	(0.025)
Log # of products viewed	0.032***	0.085***	0.067***	0.088***
	(0.010)	(0.008)	(0.009)	(0.009)
Log Price variability stock	0.053	0.015	0.058**	0.040
	(0.041)	(0.029)	(0.027)	(0.025)
Fixed-effects				
User	✓	✓	✓	✓
Product	✓	✓	✓	✓
Year week	✓	✓	✓	✓
Day of week	✓	✓	✓	✓
Hour	✓	✓	✓	✓
Fit statistics				
Observations	1,144,105	1,144,105	1,144,104	1,144,104
Pseudo R^2	0.402	0.316	0.280	0.255
Log-Likelihood	-369,997.9	-331,408.7	-327,646.8	-343,377.2

Clustered (User & Product) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

G.5 Reference prices

Table G17 reports estimates when the current price deviates (or not) from the reference price, defined as the price of the last purchase. Note that the reference price is user-product-time specific. We find that the effect of PVS manifests when the price deviates from the reference price. This is exactly what we would expect if consumers are responsive to price changes.

Table G17: Reference prices: equal price and different price

Dependent Variable:	Units	
	Equal price buy	Different price buy
Model:	(1)	(2)
Variables		
Log price	-0.433***	-0.713***
	(0.062)	(0.068)
Log price x Log price variability stock	-0.015	-0.031**
	(0.009)	(0.014)
Log # of prior purchases	-0.061***	-0.096***
	(0.010)	(0.014)
Log # of visits	0.036*	0.005
	(0.019)	(0.027)
Log # of products viewed	-0.002	0.019*
	(0.007)	(0.011)
Log Price variability stock	0.025	0.074**
	(0.022)	(0.033)
Fixed-effects		
User	✓	✓
Product	✓	✓
Year week	✓	✓
Day of week	✓	✓
Hour	✓	✓
Fit statistics		
Observations	192,765	91,215
Pseudo R^2	0.405	0.410
Log-Likelihood	-152,154.9	-65,317.1

Clustered (User & Product) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

H Online Experiments: Additional Analyses

H.1 Robustness Specifications

We estimate an interacted model to test whether algorithmic pricing exacerbates price sensitivity, as follows:

$$\log(Y_{it}) = \beta_0 + \beta_1 \log(P_{it}) + \boldsymbol{\beta_2} \log(P_{it}) \times \text{High PV}_i + \beta_3 \text{High PV}_i + \epsilon_{it} \tag{4}$$

where Y_{it} and $P_{i,t}$ denote the quantity and price, respectively; High PV_i is an indicator variable that takes value 1 if user i was assigned to the online shopping simulation with algorithmic prices (and 0 otherwise). Our object of interest is β_2, which captures to what extent price elasticity varies with price variability.

Table H18: Algorithmic Pricing and Price Sensitivity—Online Experiments

Model	Gaussian (1)	Gaussian (2)	Poisson (3)	Mixed-Effects (4)
ln Price	-0.654***	-0.456***	-0.901***	-0.481***
	(0.036)	(0.052)	(0.130)	(0.06)
ln Price × High PV		-0.374***	-0.618***	-0.430***
		(0.071)	(0.174)	(0.076)
High PV		0.637***	1.025***	0.731***
		(0.121)	(0.287)	(0.129)
Constant	1.626***	1.288***	0.851***	1.330***
	(0.060)	(0.088)	(0.218)	(0.094)
Fit statistics				
Observations	7,596	7,596	7,596	7,596
R^2	0.042	0.046	-	-

One-way (User) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The results are presented in Table H18. Consistent with the field findings, column (2) shows that participants exhibit a more price-elastic demand when exposed to prices with high variability. Additionally, as per columns (3) and (4), the results are robust when estimating a Poisson model or a mixed effects model with participants' random intercepts, respectively.

Additionally, a mediation analysis using Model 4 (Hayes, 2017) with 5,000 bootstrap samples was conducted to test whether the relationship between participant-level price elasticity (in absolute value) and the price variability condition operates via price importance. Indeed, algorithmic vs. non-algorithmic pricing was significant (b = 0.63, SE =

0.13, p = 0.001), indicating that it significantly influences participants' price importance. Furthermore, the effects of pricing condition on participants' price elasticity are mediated by the importance to prices. There is a significant indirect effect of the pricing condition on participants' price elasticity through price importance (b = 0.15, SE = 0.06, p = 0.017, 95%CI [0.33, 0.31]). A visual summary is shown in Figure H3.

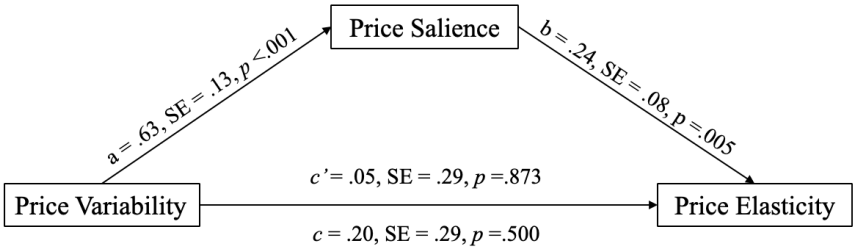


Figure H3: Price Salience Mediates Price Sensitivity

H.2 Specification of the price recall test

We test for price salience using a price recall test which we operationalize using the following construct. Consider a participant i who answers X_i; we define recall R_i as follows:

$$R_i = \begin{cases} 1, & \text{if} \quad X_i = P^*; \\ 0, & \text{otherwise} \end{cases}$$

where P^* is the correct price of the new product. Therefore, the proportion of correct participants in each treatment condition is: $p_{\text{High-PV}} = \frac{1}{N_{\text{High-PV}}} \sum_i R_i$ for algorithmic prices and $p_{\text{Low-PV}} = \frac{1}{N_{\text{Low-PV}}} \sum_i R_i$ for non-algorithmic prices. Panel (b) of Figure 8 in the main text shows the result graphically.

Furthermore, we report a robustness result to the price recall test. In particular, we classify a participant as correctly recalling the price when the recall price is within 10 cents. The results, shown in Figure H4, are similar. A Welch's two-sample t-test revealed a significant difference in means for the algorithmic pricing condition and non-algorithmic pricing condition (t(622.54) = 2.93, p = 0.003). Moreover, a proportions test indicates that the proportion of participants who recalled the price correctly was significantly different in the two groups (χ^2 = 8.0, $p = 0.005$).

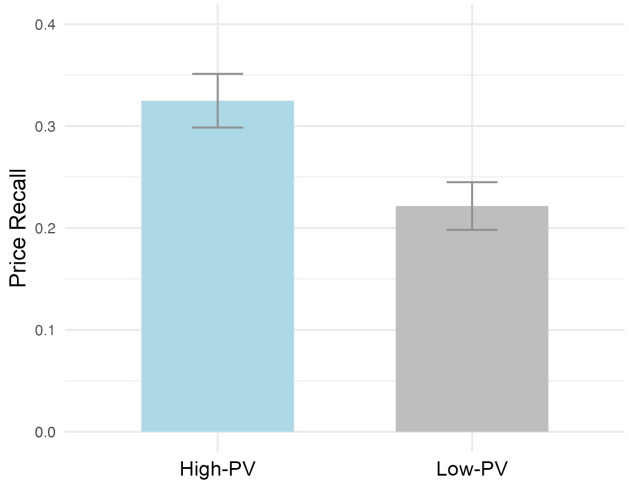


Figure H4: Algorithmic Pricing and Price Salience

H.3 MBA Classroom

Next, we report robustness results from an experiment done in an MBA classroom. The experiment covers 139 distinct students (self-reported average age of 29.8 and 68% male), 48% randomly assigned to algorithmic prices, and 52% randomly assigned to non-algorithmic prices. To avoid monetary payouts with students, while making the experiment incentive-compatible, we offered a ceramic coffee mug to the best participants in terms of units bought and savings.

The results, shown in Table H19, are similar. We find that participants in the high price variability condition experience a higher price sensitivity, compared to participants in the low price variability condition.

Table H19: Algorithmic Pricing and Price Sensitivity—Online Experiments

Model	MBA Classrooom Gaussian (1)	Poisson (2)
ln Price	-0.373***	-0.126***
	(0.076)	(0.017)
ln Price × High PV	-0.515***	-0.187***
	(0.114)	(0.033)
High PV	0.859***	0.827***
	(0.196)	(0.143)
Constant	1.236***	0.733***
	(0.135)	(0.086)
Fit statistics		
Observations	1,656	1,656
R^2	0.046	-

One-way (User) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Next, we test the effect of price variability on price recall. More precisely, whether the proportion of correct responses is higher in the algorithmic pricing condition. We classify a participant with a correct response if their answer was within 10% of the correct price.

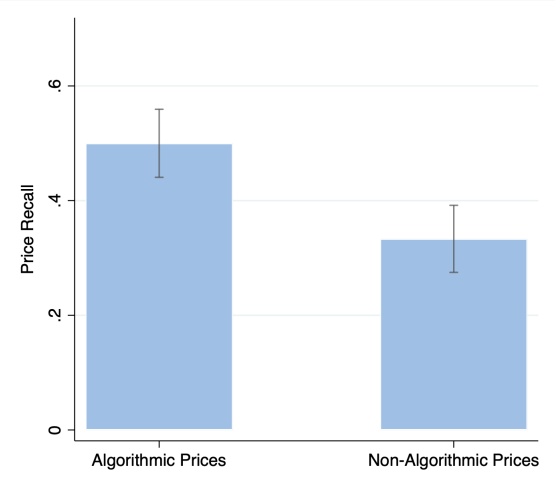


Figure H5: Algorithmic Pricing and Price Salience

We find evidence that algorithmic pricing makes price more salient. A visual summary is depicted in Figure H5: the fraction of correct responses is significantly higher under algorithmic prices, relative to non-algorithmic prices (bars are SEs). The two-sample proportions test ($z = 1.98, p < 0.05$) and Wilcoxon rank-sum test ($z = 1.97, p < 0.05$) statistically confirm that participants exposed to algorithmic prices are more likely to

recall the price correctly. Additionally, we estimate a linear model, namely $\text{Recall}_i = \beta_0 + \beta_1 \text{High PV}_i + \epsilon_i$, where Recall_i is an indicator variable that takes value 1 if user i correctly recalled the price (or 0 otherwise). The coefficient of interest is 0.167 ($p < 0.05$). In summary, the evidence supports price salience as the process through which high price variability increases price sensitivity. Nonetheless, we caveat that the existence of price salience does not preclude the role of other behavioral phenomena. We hope these results generate further research about the interaction of algorithmic pricing and consumer behavior.

I Theoretical Illustration

How do consumers' price sensitivity react to the high price variability driven by algorithms? Below, we articulate a toy model showing that the effect on price sensitivity is ambiguous, as it depends on two conflicting forces. To simplify the discussion, we focus on two behavioral phenomena, acknowledging that further mechanisms can coexist and future work can enrich this model by including such additional behavioral dynamics.

Salience. Increasing the frequency of price changes makes the price attribute more salient, relative to other attributes that remain static (brand, package, ingredients, etc.). The shift in relative salience can be thought of as changing the decision weights between the price and value of a product (Bertini and Wathieu, 2008; Bordalo et al., 2020; Blake et al., 2021; Aparicio and Rigobon, 2020). That price variation might attract attention to prices can be indirectly related to evidence that salient, visual attributes tend to be overweighted (Krider et al., 2001; Folkes and Matta, 2004). Return to Figure 1: a consumer exposed to this kind of price variability might be more attentive to price changes, and thus become *more price-sensitive*.

Signal-to-Noise Jamming. Consumers retrieve (or form) an anchor price and compare it with the current price. Typically, the price anchor is formed and updated upon exposure to past prices of the same product, advertised prices, or reference products in the category (Vanhuele and Drèze, 2002; Jindal and Aribarg, 2021; André et al., 2022). Increasing the frequency of price changes exposes consumers to a complicated price path, iterating between many distinct prices (Aparicio et al., 2023). It is unclear what anchor consumers form from this "distribution" of prices. For instance, customers might become habituated (Wathieu, 2004; Rankin et al., 2009) to price changes, and thereby accept future price variability and thus become less responsive to price changes. As a result of jamming notions of good/bad deals, consumers might become *less price-sensitive*.

With these ideas in mind, consider the following theoretical illustration. A consumer maximizes a quasi-linear utility function (Lilien et al., 1995; McAfee and te Velde, 2008; Cohen et al., 2021):

$$\max_{x_1} a_0 x_1^{-1/\nu} + x_2 \text{ subject to } \tilde{p}x_1 + x_2 \leq B$$

Where $-\nu$ is the constant elasticity of demand ($\nu > 1$), x_1 denotes the focal product, x_2 denotes the numeraire good (price normalized at 1), and B is a monthly budget. Looking at the budget constraint, $\tilde{p}$ denotes the *perceived* price of x_1, where $\tilde{p} \equiv \phi + p$. That is, the perceived price is increasing in the actual price (p) but it includes a price-variability effect (ϕ). We can state the following result.

Lemma. *The sign of the relationship between the elasticity of demand and algorithmic price variability (i.e., $\partial\eta/\partial\phi$) is ambiguous.*

To see this, we follow Finkelstein (2009) and distinguish between the elasticity of demand with respect to the perceived price and with respect to the actual price, that is to say, $\tilde{\eta}$ and η, respectively. Recall that $\tilde{\eta} = \frac{\partial x_1}{\partial \tilde{p}} \frac{\tilde{p}}{x_1} = \nu$. Additionally, $\frac{\partial \tilde{p}}{\partial p} = \frac{\partial (p+\phi)}{\partial p} = 1$ if the price level does not depend on the variability. Therefore:

$$\eta = \frac{\partial x_1}{\partial p} \frac{p}{x_1} = \frac{\partial x_1}{\partial \tilde{p}} \frac{\partial \tilde{p}}{\partial p} \frac{p}{\tilde{p}} \frac{p}{x_1} = \nu \frac{p}{\tilde{p}} \tag{5}$$

We are not interested in the demand elasticity itself but in the delta elasticity with respect to variability. Thus, we differentiate Eq. (5) with respect to ϕ: $\frac{\partial \eta}{\partial \phi}$. The sign of this relationship determines whether price variability exacerbates or attenuates price sensitivity.

$$\frac{\partial \eta}{\partial \phi} = \nu p \frac{\partial (p+\phi)^{-1}}{\partial \phi} = \underbrace{\overbrace{\nu}^{-} \overbrace{p}^{+} \overbrace{\frac{-1}{(p+\phi)^2}}^{-}}_{+} \underbrace{\phi'}_{+/-} \tag{6}$$

We observe that the relationship between the elasticity of demand and algorithmic price variability is ambiguous. The sign in Eq. (6) is determined by $\phi' \lessgtr 0$. In summary, it is an empirical question of whether algorithmic variability exacerbates or mitigates consumers' price sensitivity. We conclude that (a) when $\phi' < 0$ then signal-jamming leads to less price-sensitive demand, and (b) when $\phi' > 0$ then salience leads to more price-sensitive demand.

J Eye-Tracking: Additional Evidence

As previously discussed, salience can be thought of as relatively more attention. We obtain another set of evidence that is consistent with the role of price salience. Digital screens are often placed in physical stores (e.g., supermarkets, gas stations, and fashion stores) to advertise selected products of the assortment. We collaborate with a European marketing analytics company that manages the content of these campaigns with its partner retailers. Throughout a period of approximately two months, the company placed regular advertisements on those digital screens—in some cases with prices and in some other cases without prices. Importantly, the screen is equipped with eye-tracking technology that records consumer-level eye views and time spent viewing.

The eye-tracking sensor allows testing whether prices increase attention. Our empirical strategy resembles prior work in which the salience of an attribute drives attention to that attribute (Duncan, 1984; Folkes and Matta, 2004), and time is used as a measure of attention (Townsend and Kahn, 2014; Cian et al., 2015).[11]

We test whether showing prices on the screens captures additional signage attention (controlling for the number of eye views). In total, the data includes 3,570,646 distinct eye-views and 42 digital campaigns throughout two months. The average per-person view time of a screen, conditional on viewing, is approximately 7 seconds. Let v_{it} be the total number of views to screen i on day t and let t_t be the total time spent viewing screen i on day t. Time is measured in (log) milliseconds. The measure of interest is $\tau \equiv \frac{t_{it}}{v_{it}}$, i.e. the time spent per eye view. We then estimate the following model:

$$\tau_{it} = \beta_0 + \beta_1 \text{Price Displayed}_i + \delta_t + \gamma_s + \epsilon_{it} \tag{7}$$

where Price Displayed$_i$ is an indicator variable that takes value 1 when the screen i contains a price (and 0 otherwise); and δ_t and γ_s denote day- and store- fixed effects, respectively.

[11] We asked our partner company to augment this experimental data with a *price change*, i.e. record eye-tracking when a price changes on the screen. Unfortunately, this option was unfeasible in our setting, but it is an interesting question for further research.

Table J20: Eye-Tracking and Price Salience

	Attention Time
Price Displayed	0.110***
	(0.014)
Fixed-effects	
Store and Day	
Fit statistics	
Obs.	140,011
R^2	0.153

Table J20 shows the results. When the advertisements on digital screens contain prices, time spent viewing the screen significantly increases by 11.5% (exp(0.11)-1, $p < 0.01$). Once again, this evidence echoes the idea that price is a product feature prone to be salient; furthermore, price variation would presumably capture even more "bits" of attention and thereby heighten the role of price salience. Further research, perhaps in a laboratory setting with the availability of fMRI technology (like Karmarkar et al. (2015)), is needed to better trace out the behavioral decision-making process. For our purpose, we find this evidence reinforcing the facts about algorithmic pricing and price sensitivity, and its intersection with price salience.

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