Algorithmic Pricing and Consumer Sensitivity to Price Variability*

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Abstract

Artificial Intelligence (AI) automates human decisions. Algorithmic pricing, a form of AI, sets prices by a computer. It is now common currency in ride-hailing, travel, drugs, gasoline, online goods—And great price variability characterizes all those settings. However, little is known about how consumers respond to encountering frequently changing prices. This paper uses clickstream data from an online retailer in the U.S. that varied pricing methods to examine effects of frequently-changing prices on purchase behavior. The evidence shows that exposure to price variability exacerbates price sensitivity. These findings are confirmed in online lab experiments. Additionally, an underlying mechanism is price salience.

Keywords— algorithmic pricing, price variability, price sensitivity, price salience, experiments
JEL— L11, L21, L81, D22, D91

* Author names are in alphabetical order.

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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. In this paper, we collaborate with this retailer to address the following question: How do consumers react to algorithmic pricing?

Artificial Intelligence (AI) allows automating decisions that were previously made by humans (Brynjolfsson and McAfee, 2014; Ford, 2015; Agrawal, Gans, and Goldfarb, 2018). Algorithmic pricing is one scope of AI: price automation. It can be broadly defined as a formula to set prices by a computer. The formula can be a simple price-matching or an advanced learning process. It is known that algorithmic pricing has been expanding across industries and channels. What used to be a specialized feature of airline tickets (McAfee and Te Velde, 2006), is now taking off in ride-sharing platforms (Chen, 2016; Cohen, Hahn, Hall, Levitt, and Metcalfe, 2016; Allon, Cohen, and Sinchaisri, 2018), gasoline markets (Assad, Clark, Ershov, and Xu, 2020), allergy drugs in online retailers (Brown and MacKay, 2019), durable goods marketplace (Chen, Mislove, and Wilson, 2016; Cavallo, 2018), and groceries (Aparicio, Metzman, and Rigobon, 2021). See Aparicio and Misra (2022) for a literature review.

While the price algorithm's formula can disparately vary across firms, most algorithms have something in common: the empirical outcome is *high price variability* (Chen, Mislove, and Wilson, 2016; Brown and MacKay, 2019; Assad, Clark, Ershov, and Xu, 2020; Cavallo, 2018; Aparicio, Metzman, and Rigobon, 2021). In fact, high price variability is most typically used to infer adoption/usage of algorithmic pricing in the field (Aparicio and Misra, 2022). Intuitively, it would be somewhat unusual to have institutional guidance about each time a manager changes a lever of the price formula.[1] And again, ride-hailing, airlines, Amazon's marketplace, are all stylized examples of high-frequency price changes.

Indeed, sellers that adopt algorithmic pricing are found to update prices several times per day. For example, Amazon is known to change prices ~2.5 million times a day or, equivalently, the price for a product listed on Amazon changes every 10 minutes on average (Business Insider, 2018). Comparable examples from other industries include "Smart Pricing" by Airbnb (Airbnb, 2017) and "Surge Pricing" by Uber (Dholakia, 2015). (Uber's prices change as frequently as every three to five minutes (Washington Post, 2015).)

The empirical setting of this paper echoes those examples. We obtain clickstream and purchase data from an online retailer in the United States that implemented algorithmic pricing in its platform. To further build intuition, Figure 1 shows many compelling examples. In fact, roughly 1,200 products exhibit at least one price change in the day. This makes it visually evident that algorithmic pricing automates, and replaces, the work of a manager—it is infeasible to

[1] Time-series price variability is a key dimension of AI and pricing, but it is not the only one. Firms may want to use AI pricing for sales force or chat bots recommendations (Cui, Li, and Zhang, 2022; Karlinsky-Shichor and Netzer, 2019).

manually update thousands of prices every day.

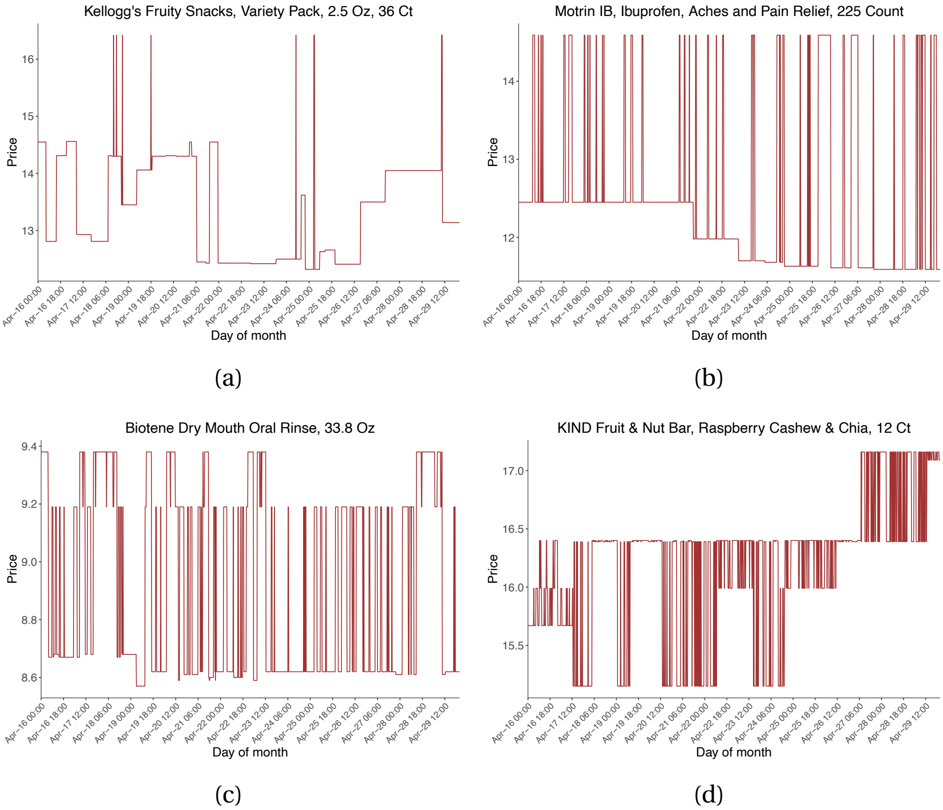


Figure 1: Algorithmic Pricing in an Online Grocery Platform

Despite the growing usage of algorithmic pricing (and vendors that offer AI pricing to small sellers for a monthly fee, see Musolff (2021)), we know little about *how consumers react* to the strikingly high price variability. We contribute to the human/machine intersection by studying whether and how consumers' price sensitivity reacts to price algorithms, as measured by the exposure to a heightened frequency of price changes or multiple unique prices. Price sensitivity remains a fundamental question in the economics and marketing literature. To illustrate, early papers on advertising were absorbed about the connection between advertising and price sensitivity (Dorfman and Steiner, 1954; Becker and Murphy, 1993)—and to date, this question remains contested (Sethuraman, Tellis, and Briesch, 2011). And while price sensitivity is a key object of interest across the literature, its intersection with algorithmic pricing is relatively underdeveloped. In Section 2 we review the related literature and map our contribution in this space.

We begin with a theoretical illustration of how algorithmic pricing can shift consumers' price sensitivity in Section 3. The conceptual framework captures an *ambiguous* effect between price salience and price obfuscation. On the one hand, algorithmic pricing heightens price salience. We connect to Chetty, Looney, and Kroft (2009); Bordalo, Gennaioli, and Shleifer (2013, 2020), who study consumer choice in the context of boundedly rational consumers and salience effects. Relatedly, Finkelstein (2009); Busse, Lacetera, Pope, Silva-Risso, and Sydnor (2013); Hastings and Shapiro (2013); Busse, Pope, Pope, and Silva-Risso (2015); Aparicio and Rigobon (2020); Blake, Moshary, Sweeney, and Tadelis (2021) find empirical support to the role of salience in offline and online markets. On the other hand, algorithmic pricing obfuscates the price anchor, namely "jams" the signal-to-noise for good or bad deals. Such effect is possible given findings about price cues, limited price recall, and constrained attention across attributes (Monroe, 1973; Dickson and Sawyer, 1990a; Lichtenstein, Ridgway, and Netemeyer, 1993; Thomas, Simon, and Kadiyali, 2010; Caplin and Dean, 2015; Jung, Kim, Matejka, Sims, et al., 2019). The novelty lies in conceptualizing the ambiguous effect of algorithmic pricing through the lens of price salience and price anchors. Therefore, theoretically speaking, it is unclear whether algorithmic pricing attenuates or amplifies price sensitivity.

With these ideas in mind, we proceed in Section 4 to describe the field setting. We collaborate with an online retailer in the United States that utilized algorithmic pricing in the platform to study how price variability affects consumer behavior. Overall, the data cover more than 3 thousand products, 3.4 million purchases, and 784 thousand customers during a 15-month period. Critically, the clickstream dataset covers both search and purchases, allowing us to track patterns of visitation and purchases across and within users. This is important because, as we explain later, we exploit the fact that distinct consumers browsed the same product(s), but had different price and price variability exposures over time. We emphasize: customers have different exposure to price variability even if they are purchasing or browsing identical products.

Two core empirical strategies are used to estimate the effect of price variability on price sensitivity:

1. In Section 5, we build intuition by estimating aggregate models at the weekly–product level (to mimic weekly scanner data), distinguishing product–week combinations with high vs. low price variability. Overall, we find own-price elasticities that are qualitatively similar with prior work (Anderson and Simester, 2008; Hitsch, Hortacsu, and Lin, 2019; DellaVigna and Gentzkow, 2019; Semenova, Goldman, Chernozhukov, and Taddy, 2017; Aparicio, Metzman, and Rigobon, 2021). And importantly, we report a significantly more price-sensitive demand when algorithmic pricing is most intensively updating prices.

2. In Section 6, we build a model of customer-level exposure to price variability. Here, we exploit the fact that pricing is not personalized, and therefore, customers get exposed to severe/moderate price variability "as-randomly."[2] Additionally, we implement an instrumental variables approach (using a customer's *unseen* prices) to pin down the causal effect of frequently changing prices. Once again, we report a consistent pattern: price variability exacerbates price sensitivity.

In practice, most firms rarely personalize algorithmic pricing for some users and not for others. Doing so would require setting different price *sequences* for each user–product throughout

[2]While we control for user and other granular fixed-effects to absorb concerns of customer types, strategic behaviors, etc., we also show that customers' visitation patterns with respect to prices are as-good-as-random: customers are equally likely to encounter a high/low price or to arrive before/after a price change.

their visits, an ideal but unlikely experiment. Therefore, we conduct a series of online lab experiments to test the key effect of algorithmic pricing in a controlled environment.[3] We implement a between-subject design in which participants are randomly assigned to one of two treatment conditions: stable pricing and algorithmic pricing. Participants in each cell are asked to simulate online purchases over a set of periods, and the price fluctuates from period to period. Importantly, the purchase decisions are incentive-compatible because participants' payoff depends on their units bought and savings—which encourages participants to carefully react to price changes as they would in real life. We find consistent evidence that participants are more price sensitive when exposed to higher price variability. The online experiments are discussed in Section 7.

Returning to the conceptual framework, the online experiments allowed us to show that *price salience* is a key behavioral mechanism triggered by price variability. We operationalize salience as recall, following vast tradition in the literature (Alba and Chattopadhyay, 1986; Kissler, Herbert, Peyk, and Junghofer, 2007; Finkelstein, 2009; Kroft, Lange, and Notowidigdo, 2013; Gaspelin, Leonard, and Luck, 2015). Participants exposed to high price variability experience higher price recall, compared to participants with low price variability. Additionally, we obtain secondary data from a technology company that manages digital screens. Using eye-tracking technology installed in digital screens (placed in physical stores), we find that showing prices captures more attention, compared to signage without prices—reminiscent of Jacoby (1984)'s "bits" of attention. We interpret this evidence as reinforcing the role of price salience, i.e. if prices were to actually *change* on the screens, the attention (salience) would very likely be much greater. While we emphasize the role of salience, we make no claim that it precludes other processes to operate as well—an interesting question for future research.

As we expand in Section 8, overall, our work unveils a side effect of algorithmic pricing: consumers are not indifferent to price variability; it modifies shopping behavior and increases price sensitivity. These findings are critical because, intuitively, a more price-sensitive demand "eats" some of the benefits that presumably could have been extracted with a static demand. Because algorithmic pricing presumably makes firms better off (Aparicio and Misra, 2022), what can they do about it? This side effect could be utilized as an "input." That is, a platform may want to *personalize* algorithmic pricing to mitigate behavioral reactions (Dubé and Misra, 2023).

For example, suppose that an algorithm determines an optimal price of $3.17. Moreover, suppose that user A has recently visited that product twice, and on those occasions, the price was $3.09 and $3.99. From the firm side, it may be optimal to coarsen the price for user A—to the already-seen $3.09 rather than $3.17—while show $3.17 for user B. In statistical parlance, this problem may be articulated as adding a penalty or regularization term on the number of price changes the algorithm is allowed to make. The new price may be a "better" price but the trade-off needs to be judged after netting out the negative impact of increased price sensitivity. This insight further fuels prior work about various ways retailers can implement customized promotions (Shaffer and Zhang, 1995; Rossi, McCulloch, and Allenby, 1996; Zhang and Krishnamurthi,

[3] We run experiments in an MBA classroom, in Prolific, and in MTURK. Sometimes the literature refers to these settings as laboratory experiments. We refer to them as online lab experiments, though we note they did not take place in an actual research laboratory.

2004; Zhang and Wedel, 2009; Dubé and Misra, 2023; Zhang, Dai, Dong, Qi, Zhang, Liu, Liu, and Yang, 2020; Smith, Seiler, and Aggarwal, 2022). Taking a step back, our work encourages scholars to be mindful that, as AI keeps breaking the scene, the human/algorithm intersection shall also become increasingly important.

2 Related Literature

In what follows, we outline our relation and contribution to various strands of literature.

Price Algorithms. A key focus of the AI pricing literature is whether, and how, the adoption of algorithmic pricing can alter competition incentives across rival firms (Miklós-Thal and Tucker, 2019; Calvano, Calzolari, Denicolò, and Pastorello, 2019; Brown and MacKay, 2019; Hansen, Misra, and Pai, 2021; Asker, Fershtman, and Pakes, 2021). Are competing price algorithms learning from each other and arriving to collusive, supra-competitive prices? While the empirical evidence is slim (and mixed), overall firms are responsive to each other's prices (Brown and MacKay, 2019; Assad, Clark, Ershov, and Xu, 2020; Aparicio, Metzman, and Rigobon, 2021). Our data covers a single (leading) platform and therefore do not directly speak to concerns of price collusion; however, our findings of heightened price sensitivity pose attractive implications for future research. For example, whether/how competing algorithms learn and input effects of price sensitivity, and whether those effects moderate potential collusion. Another body of literature shows that algorithmic pricing triggers reactions from sellers and buyers. The work of Allon, Cohen, and Sinchaisri (2018); Castillo (2020); Angrist, Caldwell, and Hall (2021); Cohen, Fiszer, and Kim (2022) studies drivers' and riders' strategic responses to surge pricing in ride-hailing. Huang (2021) studies hosts (sellers) responses to Airbnb's "Smart Pricing" tool. To our knowledge, no studies have studied consumer-level exposure to algorithmic pricing in a recurrent-purchase setting as online groceries and their effects on price sensitivity. See Aparicio and Misra (2022) for a review of the AI pricing literature.

Price Sensitivity. There is a century-long literature about price elasticities in marketing and economics. In our context, it is helpful to connect with a stream of papers, typically using weekly scanner data, which study household's inter-temporal problem and the effects of various price policy changes. The objects of interest tend to be the own-price and cross-price elasticities, and how consumers respond to temporary/permanent price changes. These include dynamic or reduced-form models (Gupta, 1988; Chintagunta, 1993; Boulding, Lee, and Staelin, 1994; Mela, Gupta, and Lehmann, 1997; Mela, Jedidi, and Bowman, 1998; Swait and Erdem, 2002; Pauwels, Hanssens, and Siddarth, 2002; Erdem, Imai, and Keane, 2003; Anderson and Simester, 2004; Elberg, Gardete, Macera, and Noton, 2019) and structural models (Hendel and Nevo, 2004, 2006; Erdem, Keane, and Sun, 2008a). We emphasize that these papers do not consider online dynamic or algorithmic pricing. The recent work of Zhang, Dai, Dong, Qi, Zhang, Liu, Liu, and Yang (2020) tests targeted discounts in the shopping carts and finds it encourages promotion-seeking behaviors.

Behavioral Reactions. Interestingly, there is work connecting algorithmic pricing and consumer behavior. Haws and Bearden (2006) and Weisstein, Monroe, and Kukar-Kinney (2013) show that unusual price differences may evoke feelings of unfairness and thereby reduce willingness-to-pay.[4][5] These findings are obtained in the context of laboratory experiments, and therefore highlight the need to understand more "realistic shopping environments and under conditions of higher involvement" (Haws and Bearden, 2006). The theoretical work of Cohen, Elmachtoub, and Lei (2022) inputs fairness concerns to optimize pricing. Finally, although not in the context of algorithmic pricing, prior studies have shown that price movements can trigger customer antagonism (Rotemberg, 2005; Anderson and Simester, 2010). To illustrate, Rotemberg (2005)'s seminal work writes: "Increases in price that do not correspond closely to increases in costs are likely to trigger consumer anger." While fairness is beyond of our scope, our work contributes to this debate by reporting novel evidence from online experiments about the intersection of price salience and AI pricing.

In summary, we build on a rich literature about AI pricing and consumer reactions to pricing. We explore two key underdeveloped questions: intersection of algorithmic pricing and price sensitivity, and mechanisms of price salience.

3 Theoretical Illustration

Does a consumer's price sensitivity react to the heightened price variability driven by algorithms? Before we discuss any empirical evidence, it is helpful to think about this question from a conceptual perspective. Here, we might envision the role of two conflicting effects.

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, Gennaioli, and Shleifer, 2020; Blake, Moshary, Sweeney, and Tadelis, 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 over-weighted (Krider, Raghubir, and Krishna, 2001; Folkes and Matta, 2004). Return to Figure 1: a consumer exposed to this kind of price variability might be more attentive to prices changes, and thus become *more price-sensitive.*

Signal-to-Noise Jamming. Consumers retrieve (or form) a notion of reference price and compare it with the current price. Abundant research has explored how a price anchor is generated and the extent to which it can be manipulated by various price presentation strategies (Monroe, 1973; Lichtenstein, Ridgway, and Netemeyer, 1993; Kalyanaram and Winer, 1995; Anderson and Simester, 2003; Amaldoss and He, 2018; Jindal and Aribarg, 2021). Typically, the price anchor is formed and updated upon exposure to past prices of the same product, advertised prices,

[4]Some studies use the term "dynamic pricing." Throughout, we maintain the algorithmic pricing terminology.

[5]Obviously, there is a big interest of AI in behavioral sciences. See, for example, Horton (2017); Dietvorst, Simmons, and Massey (2018); Castelo, Bos, and Lehmann (2019); Luo, Qin, Fang, and Qu (2021). However, these studies relate to AI and human/machine aversion and do not speak to pricing.

or reference products in the category (Vanhuele and Drèze, 2002; Jindal and Aribarg, 2021; André, Reinholtz, and De Langhe, 2021). Increasing the frequency of price changes exposes consumers to a complicated price path, iterating between many distinct prices (Aparicio, Metzman, and Rigobon, 2021). Similarly, algorithmic pricing may modify the formation of new anchors or the acceptability of a new price (Lichtenstein, Bloch, and Black, 1988; Biswas and Blair, 1991; Rao and Sieben, 1992; Briesch, Krishnamurthi, Mazumdar, and Raj, 1997; Mazumdar, Raj, and Sinha, 2005). Meaning, frequent exposure to price variability might increase acceptability for a price change, and therefore lower sensitivity to price changes. Returning to Figure 1, it is unclear what the typical price should be. As a result of jamming notions of good/bad deals, consumers might become *less price-sensitive* to a price change.

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

$$\eta = \frac{\partial x_1}{\partial p}\frac{p}{x_1} = \frac{\partial x_1}{\partial \tilde{p}}\frac{\partial \tilde{p}}{\partial p}\frac{p}{\tilde{p}}\frac{p}{x_1} = \nu\frac{p}{\tilde{p}} \tag{1}$$

We are not interested in the demand elasticity itself, but in the delta elasticity with respect to variability. Thus, we differentiate Eq. (1) with respect to ϕ: $\frac{\partial\eta}{\partial\phi}$. The sign of this relationship determines whether price variability exacerbates or attenuates price sensitivity.

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

We observe that the relationship between the elasticity of demand and algorithmic price variability is ambiguous. The sign in Eq. (2) is determined by $\phi' \lessgtr 0$. In summary, it is an empirical question 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. In the following sections, we show evidence from the field and from online experiments that algorithmic price variability consistently exacerbates price elasticity, which supports the role of *price salience*.[6]

4 Data and Empirical Setting

4.1 Data

We collaborate with an online retailer in the United States that implemented algorithmic pricing in its platform to understand how frequently-changing prices affect consumer behavior. This empirical setting is particularly well-suited to study consumer reaction to algorithmic pricing. 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 is valuable empirically compared to scanner data which ignores visits (i.e., price exposure) that do not end with a purchase. Moreover, the recurring nature of groceries and related products renders them ideal to exploit multiple visitations over time—and thus, critically, various degrees of price exposure across consumers.

Table 1: Data Description

		Summary Statistics
(1)	Consumers	784,190
(2)	Products	3,039
(3)	Time period	15 months
(4)	Units sold	3,462,150
(5)	Top-5 categories	Household Supplies, Baby, Health & Beauty, Grocery, Pet Supplies

Table 1 reports summary statistics on the data. We focus on a subset of products that experienced algorithmic pricing and, additionally, a minimum threshold of purchase records. Overall, the data covers 3,039 distinct products across groceries, household supplies, baby products, health and beauty, and pet supplies. The data covers 15 months, 784,190 distinct consumers, and over 3.4 million units sold.

4.2 Stylized Facts of Algorithmic Pricing

We begin by presenting some key stylized facts of algorithmic pricing. These facts build intuition for the empirical identification strategy (Section 6). Moreover, provide a broader perspective of algorithms at the scale of thousands of products in online retail—e.g., updating prices for so many products can only be tacked with price automation. These facts center around price changes: (a)

[6] In Section 8 we discuss alternative, mutually non-exclusive behavioral theories to enrich our analysis.

frequency, (b) magnitude, and (c) exposure.

Fact 1: Price changes are extremely frequent

Figure 2 (and return to 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 it 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. We emphasize that these are remarkable frequencies of price changes, compared to our knowledge in the literature (Cavallo, 2018; Aparicio, Metzman, and Rigobon, 2021; Aparicio and Misra, 2022).

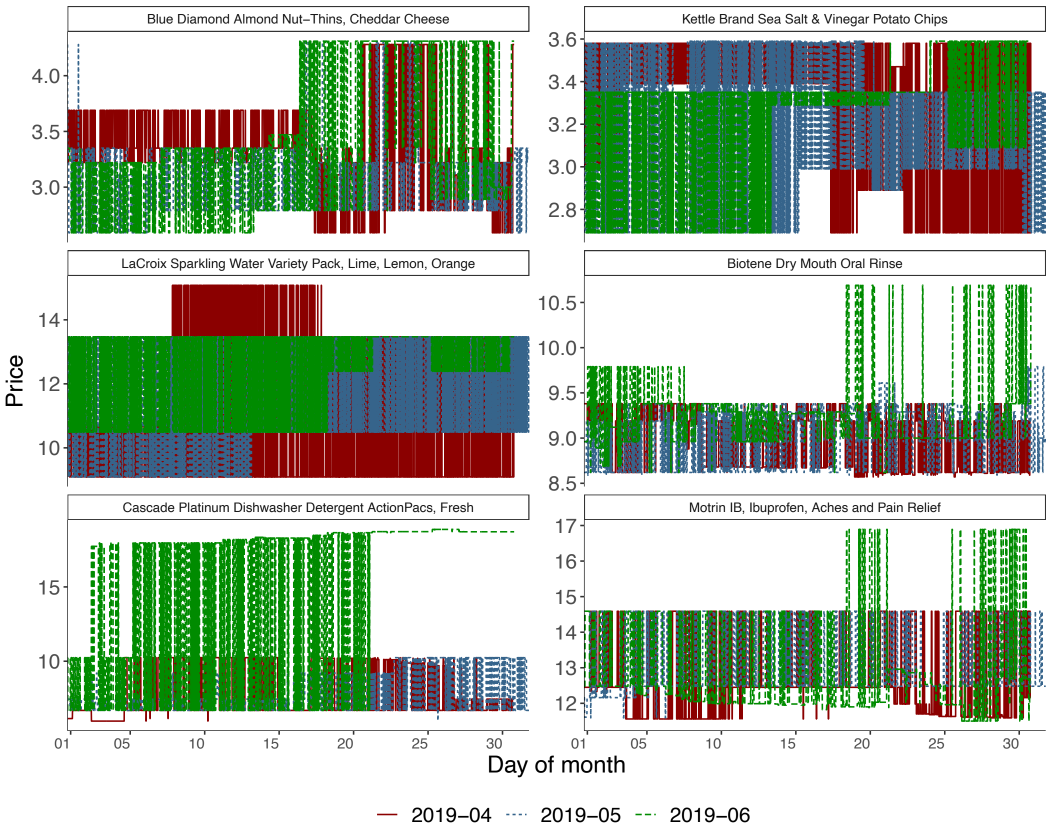


Figure 2: 15-Minute Prices Across Days of the Month (Overlapping 3 Months)

Relatively, on a typical day, ~1,200 products (out of 3,039 in our sample) change price at least once. Figure 3 shows that this number is stable throughout a given month. In addition to illustrating the price variability, Figure 3 is helpful to grasp the scope of algorithmic pricing when implemented at a large scale—i.e., algorithmic pricing automates price setting for thousands of products across all categories. Appendix A provides additional evidence across subcategories.

Overall, these facts capture a key output of algorithmic pricing: high price variability over time (Chen, Mislove, and Wilson, 2016; Brown and MacKay, 2019; Assad, Clark, Ershov, and Xu, 2020; Aparicio, Metzman, and Rigobon, 2021). As expected, and consistent with Fisher, Gallino, and Li (2018), price changes are not mechanically triggered by cost changes; Appendix A provides evidence for this along with more details on price levels and changes throughout the week and day. These facts highlight that there is no obvious timing in which prices are cheap or expensive, or in which prices are expected to remain flat.

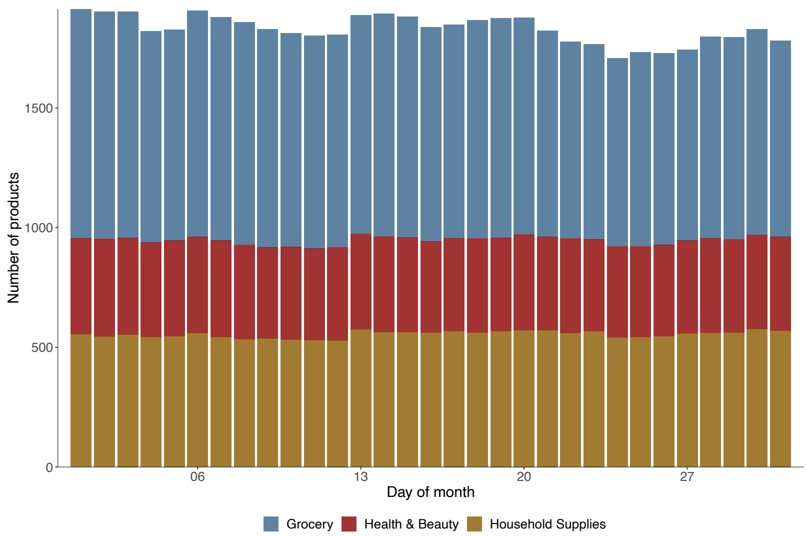


Figure 3: Number of Products with a Price Change in the Top-3 Categories

Fact 2: Price changes are small but not trivial

Algorithmic price changes are frequent but of a small size. Figure 4 shows the distribution of price changes in absolute percentage terms across products. A quarter of the price changes are less than or equal to 5% of the previous price, and roughly 70% of all price changes are within 20% of the previous price.[7] 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; Strulov-Shlain, 2021).

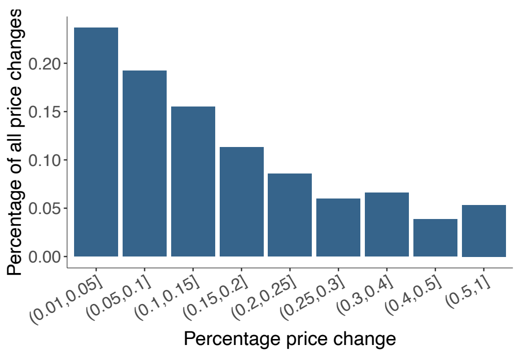
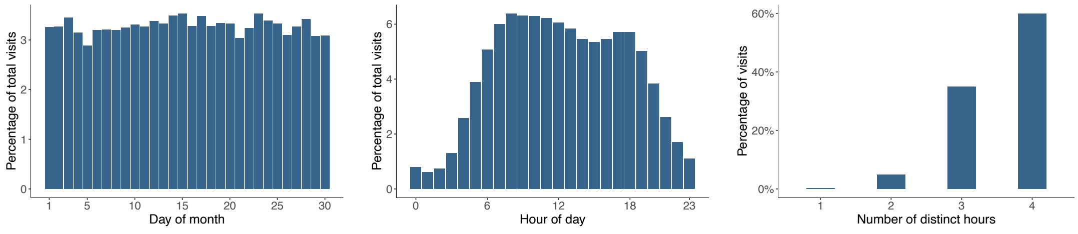


Figure 4: Cumulative Distribution of Price Changes

Fact 3: Customers Have "Haphazard" Visitations with Respect to Prices

[7]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.

What does this price variability mean to consumers? Now, it is helpful to take the customer perspective. Figure 5 shows that consumers visit the platform at different hours of the day and days of the month. Consider a customer that visits the platform four times. We ask the following: Does that customer visit the platform at the same hour? Panel (c) shows that the answer is no. An overwhelming fraction of users will visit the platform at four distinct hours (e.g., 11 am, 12 pm, 4 pm, 7 pm).

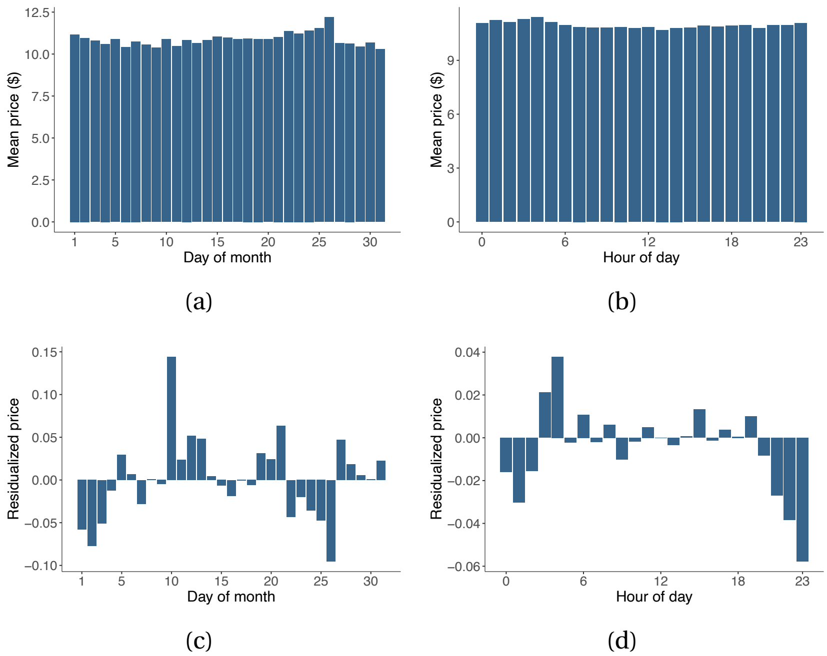


(a) User visits by day of month (b) User visits by hour of day (c) Number of unique hours a user visits conditional on visiting the retailer's website 4 times

Figure 5: Stable User-level Visitation Patterns

In a similar vein, Figure 6 shows that price levels are overall stable throughout the day and hour. Appendix A shows additional evidence of price fluctuations day and by hour, and therefore that prices are not mechanically cheap or expensive by day and by hour.

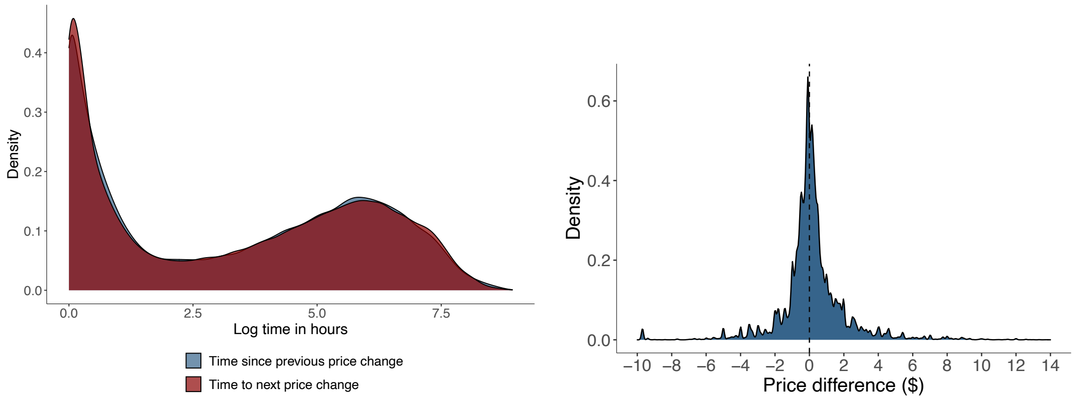
This evidence informs that consumers rarely "strategize" or "time" their visits—Or in any case, consumers should be equally likely to visit before/after a price change, or to see a cheap/expensive price. We show this next.



(a) (b) (c) (d)

Figure 6: Price Levels Throughout Days of the Month and Hours of the Day

Panel (a) of Figure 7 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 the same vein, Panel (b) shows that a customer is equally likely to encounter a high or low price, as measured by the percent difference with respect to the median price in the month. Appendix A reports robustness specifications.



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

(b) Distribution of magnitude of price changes before and after user visits. Difference is taken with respect to the median price of the product in that month

Figure 7: Users' Haphazard Visitation Patterns

In summary, we observe a shopping behavior characterized by a "haphazard" visitation pattern: consumers do not appear to—or are able to—strategize insofar the prices that they encounter are sometimes the same, or higher, or lower. Said differently, customers that browse the same product, in nearby timestamps, are exposed to different prices—and thus exposed to various degrees of price variability. Moreover, the retailer's price algorithms do not customize price levels or price changes to a particular consumer. We emphasize that a user's decision to visit the platform is obviously not random—But their haphazard visitation patterns means that their *exposure to price variability*, conditional on their visitations, may be considered as-random. The implications from Facts 1-2-3 will be helpful to estimate user-level models of price sensitivity as well as to construct instrumental variables. We discuss these analyzes next.

5 Simple Evidence from Aggregated Models

Consider a reduced form demand model similar to DellaVigna and Gentzkow (2019); Hitsch, Hortacsu, and Lin (2019) which aggregates data at the product–week level and takes the following form: $\log(Y_{jt}) = \beta_0 + \beta_1 \log(P_{jt}) + \mu_j + \tau_t + \epsilon_{jt}$; where Y_{jt} is the number of units sold for product j in week t and P_{jt} is the quantity-weighted average price for product j at time t, μ and τ are product and time fixed effects, respectively. In this section, we update this model by distinguishing customer–periods with high vs. low price variability. This operationalization resembles prior work whereby algorithmic pricing is identified upon the observed price variability in the time-series (Chen, Mislove, and Wilson, 2016; Brown and MacKay, 2019; Assad, Clark, Ershov, and Xu, 2020; Aparicio, Metzman, and Rigobon, 2021).

More specifically, for each product, a binary indicator of high price variability is defined if the week is among the top quartile distribution of price changes for that product. We then aggregate purchases at the product–week level, separately for product–weeks with high and low price variability. A variance decomposition test, shown in Appendix B, indicates that this indicator significantly explains price variation. The updated fixed effects panel is:

$$\log(Y_{jt}) = \beta_0 + \beta_1 \log(P_{jt}) + \boldsymbol{\beta_2} \log(P_{jt}) \times \text{High PV}_{jt} + \beta_3 \text{High PV}_{jt} + \mu_j + \tau_t + \epsilon_{jt} \tag{3}$$

where High PV_{jt} is a binary indicator that equals 1 for product j in week t experiencing frequent price changes. Our interest lies in $\boldsymbol{\beta_2}$: whether high price variability influences price sensitivity.

The results are shown in Figure 8. For simplicity, we report the change in the price elasticity (i.e., β_2's estimand) and report the full parameter estimates in Appendix B. A negative value indicates that demand is more price-sensitive when exposed to high price variability. We start with estimating Model 3 with OLS, regressing log units purchased on log price, the high price variability indicator, and their interaction. The change in elasticity is shown in the first bar of Figure 8.

Our main specification follows Anderson and Simester (2008) and we estimate a quasi-Poisson demand model (shown in the second bar of Figure 8). Results show an increase of $\sim 8\%$ in price sensitivity during periods of high price variability. The results are unchanged if we exclude the holiday period (mid-November to mid-January)—a time when retailers typically run multiple promotions. This key effect on price elasticity is consistent across several robustness specifications: OLS, hierarchical mixed-effects model (Gelman and Hill, 2006), and Orthogonal ML (Semenova, Goldman, Chernozhukov, and Taddy, 2017). Detailed estimates and model specifications are provided in the Appendix in Section B.

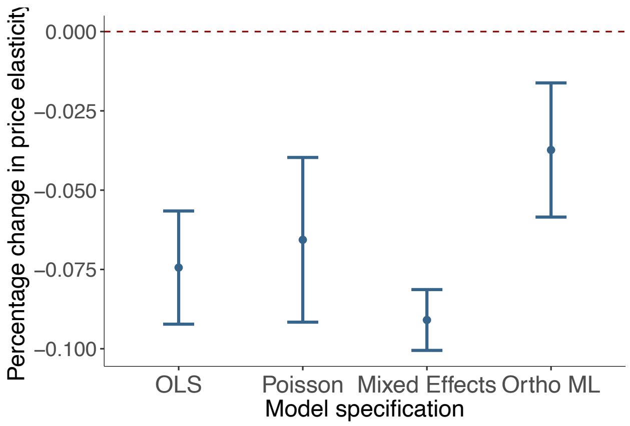


Figure 8: Increased Price Sensitivity in Periods of High Price Variability

We further use the aggregate panel to build intuition for the change in price sensitivity. We estimate a hierarchical mixed-effects model (Gelman and Hill, 2006) to allow for heterogeneity across product categories. Previous literature has used similar random effects models to study price elasticities and online consumer behavior (Hoch, Kim, Montgomery, and Rossi, 1995; Kaptein and Eckles, 2012). Mixed-effects models allow for partial pooling of information across products and categories; in our case, they efficiently estimate product-level elasticities to conduct sub-group analysis. We use a nested hierarchical approach where we allow the intercept and slopes to vary by category and by each product within that category; we also allow the intercept to vary over time. The following model is estimated using Restricted Maximum Likelihood:

$$\log(Y_{jt}) = \beta_{0cjt} + \beta_{1cj}\log(P_{jt}) + \beta_{2cj}\log(P_{jt}) \times \text{High PV}_{jt} + \beta_{3cj}\text{High PV}_{jt} + \mu_j + \epsilon_{jt} \tag{4}$$

where β_{0cjt} is the intercept that is allowed to vary by category, product, and year-week, and all three slope coefficients $\beta_{1cj}, \beta_{2cj}, \beta_{3cj}$ are allowed to flexibly vary by category and by product within a category.

The main results from the mixed-effects model are shown in the third bar of Figure 8. Once again, the effect is similar to the previous models. Reassuringly, the estimated own-price elasticities are qualitatively in line with recent studies using grocery data (Hitsch, Hortacsu, and Lin, 2019; DellaVigna and Gentzkow, 2019; Semenova, Goldman, Chernozhukov, and Taddy, 2017; Aparicio, Metzman, and Rigobon, 2021). We also find that there is a significant shift in greater price sensitivity across most products. Moreover, multilevel analysis of variance (ANOVA) shows that varying intercept and slope parameters significantly explain purchase variation. See Appendix B.

The mixed-effects models allow us to take a step further in decomposing the results across product categories. Figure 9 shows the delta price elasticity for product–weeks where users are exposed to algorithmic pricing, split by product category. For simplicity, we visualize 20 categories above the median effect (global average effect marked in red). Overall, and interestingly, we observe some but not fundamental heterogeneity across products.[8]

[8]We find similar results across types of products, e.g. cheap and expensive, high-revenue and low-revenue, or perishable and non-perishable. See Appendix C.

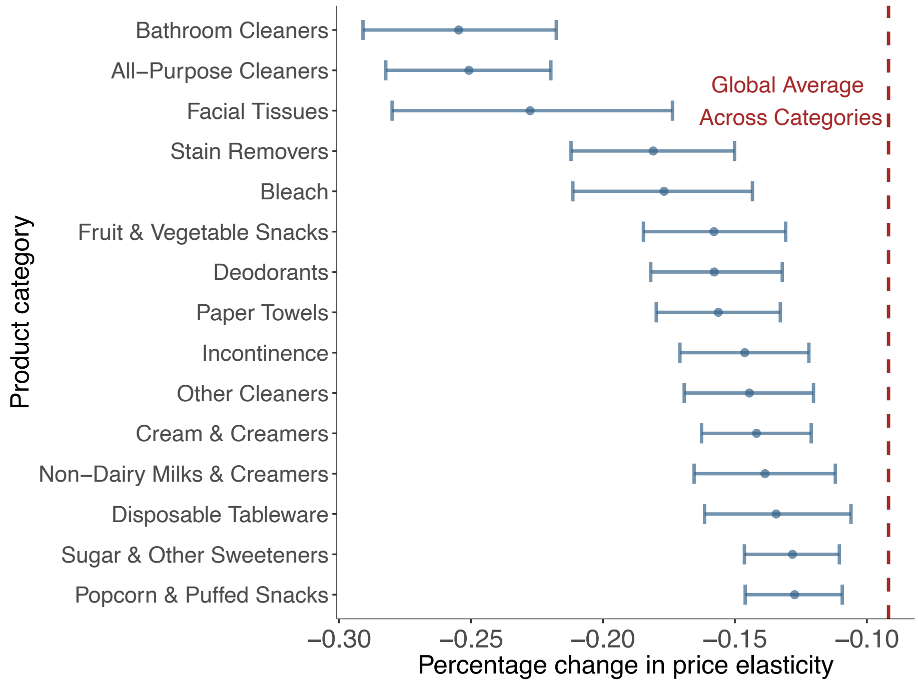


Figure 9: Hierarchical Mixed-Effects—Δ in Price Sensitivity in 20 Categories

These simple models provide a consistent takeaway: high price variability exacerbates price sensitivity. However, there are some identification questions, such as: (a) sample composition (e.g., unbalanced groups of products or users), (b) price endogeneity (e.g., the algorithm updates a price when users visit), and (c) timing endogeneity (users "time" their visits to the platform strategically). In other words, they do not allow for causal identification of the impact of algorithmic pricing on consumer behavior. Next, we exploit consumer visit-level data to identify the causal effect of algorithmic pricing on price sensitivity.

6 Consumer Exposure to Price Variability

In this section, we estimate the effect of price variability through a model that exploits user-level price exposure. This occurs because, even though users A and B visit the same product in nearby moments, users A and B happen to be exposed to different price variability, for example due to a price change right in-between their visits. Consider Figure 10, which illustrates a single user who visits a single product four times during a two-week period. Across these four visits, the user sees two distinct prices, and hence the total price variability stock is 2. However, had the user visited a few hours earlier or later, she would have seen a different price for the same product, and therefore experienced a different price variability. Consider the first visit of the user on Jan-15 at 9:15 AM. Suppose that, instead of Jan-15 at 9:15 AM, she visited the product at 8:25 AM on Jan-16. Then, all else equal, her price variability stock would have been 3.

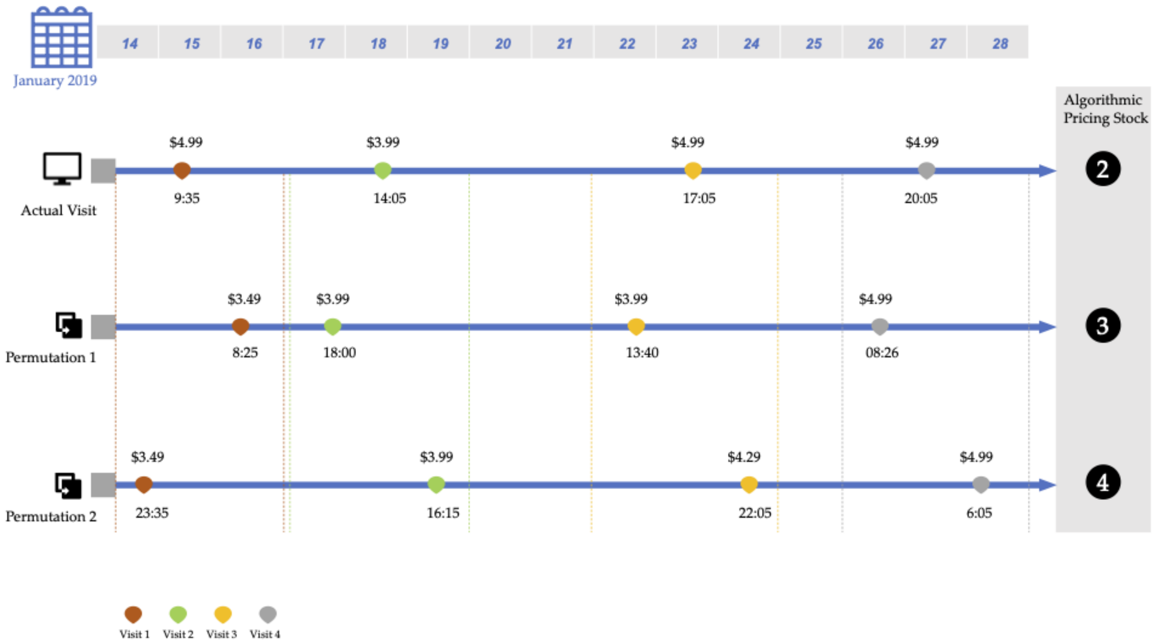


Figure 10: Illustration of Price Variability Exposure Within ± 48-Hours of Actual Visit

The clickstream data cover granular browsing and shopping clicks at the consumer level. We use it to estimate the effect of algorithmic pricing by exploiting the exposure each user had to price variability. What does "exposure" mean? To see this, it helps to begin with a model that bears resemblance to studies investigating the "stock" of advertising (Erdem, Keane, and Sun, 2008b; Shapiro, Hitsch, and Tuchman, 2021). Thinking of algorithmic pricing through the lens of advertising and price sensitivity (Dorfman and Steiner, 1954; Becker and Murphy, 1993) is helpful because algorithmic pricing cannot be reduced to a simple A/B test. Like advertising—where multiple ads matters—exposure to algorithmic pricing is also cumulative: encountering zero price changes in three visits vs. two price changes vs. three price changes matters.

Our model traces the stock of price variability that each user was exposed to, and accounts for spillovers of price variability across products over time. More formally, the user-level model is defined as:

$$Y_{ijt} = f(P_{ijt}, A_{it}, X_{ijt}; \epsilon_{ijt}) \tag{5}$$

where Y_{ijt} is the number of units of product j purchased by user i at time t and X_{ijt} are covariates that account for the user i's historical search and purchase intensity. And A_{it} is the cumulative effect of algorithmic pricing that user i has encountered until time t, operationalized as the number of unique prices that the consumer has seen over the past L days across all products that the consumer browsed more than once.[9] In the above specification, t is each individual visit to product j. Throughout, we report $L = 30$ days but the results are robust to accounting for different

[9] As an example, if the consumer 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 her algorithmic pricing stock A_{it} is two.

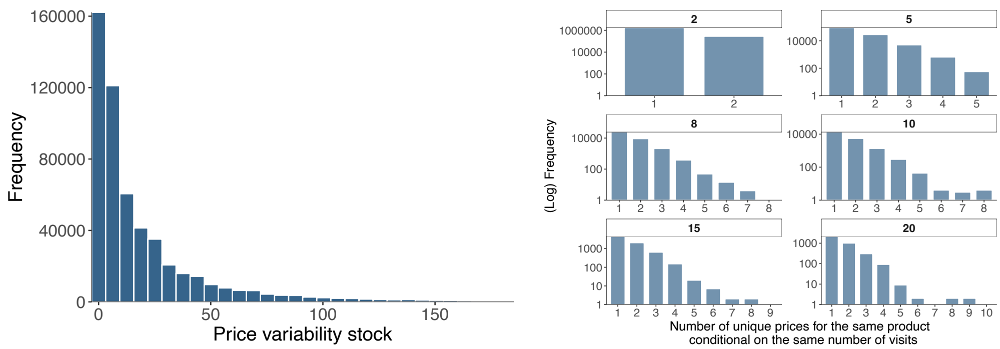
intensities of exposure to algorithmic pricing, e.g. $L \in \{7, 15, 60\}$ days.

We use the following econometric specification for the model:

$$\mathbb{P}(Y_{ijt} = y) = \frac{e^{-\lambda_{ijt}} \lambda_{ijt}^{q}}{q!}, \quad q = 0, 1, 2, \ldots$$
$$\log(\lambda_{ijt}) = \beta_0 + \beta_1 \log(P_{ijt}) + \boldsymbol{\beta_2} \log(P_{ijt}) \times A_{it} + \beta_3 A_{it} +$$
$$\delta X_{ijt} + \Gamma_i + \mu_j + \tau_w + \epsilon_{ijt} \tag{6}$$

where β_2 captures the relationship between the price variability stock (A_{it}) and price sensitivity. A negative value indicates that consumers become more price sensitive after increasing exposure to algorithmic pricing. We include stringent controls: X_{ijt} includes the total number of visits that the consumer made in the past L days, the total number of products browsed per visit, and the total number of purchases made; Γ_i denotes user-level fixed effects, μ_j denotes product fixed effects, and τ_w denotes year-week fixed effects.

Arguably, one may point out that A_{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 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 of consumers. The controls remove these concerns: the effect is identified upon variation in A_{it} that is conditional on the number of visits. In other words, the effect captures the variation within users, conditional on visiting the product the same number of times.



(a) Marginal distribution

(b) Distribution conditional on number of visits. Each panel conditions on the number of visits to a given product in the past 30 days.

Figure 11: Marginal and Conditional Distributions of Price Variability Stock for a 30-Day Period

Reassuringly, Figure 11 provides evidence of the variation of conditional A_{it}. Panel (a) shows the marginal distribution of price variability stock aggregated at the user-visit level, i.e., the level at which Model 6 is estimated. Panel (b) shows the conditional distribution of price variability stock dis-aggregated to the user-product-visit level. For instance, the top-right facet of Panel (b) shows, conditional on visiting a product five times in the past 30 days, there is variation in the price exposure, from one to five unique prices. This variation allows us to remove the role of the browsing intensity, i.e., estimates of Model 6 are conditional on visiting the same product, the same number of times.

Finally, user- and product-fixed effects control for unobserved time-invariant user and product heterogeneity, respectively. Our main specification has user, product, and year-week fixed effects. However, we show robustness of our results after including day-of-week fixed effects and hour-of-day fixed effects. This rich set of fixed effects allows us to control any unobserved artifacts of the algorithm which changes prices at different times of the day.

6.1 Fixed Effects Estimates

We estimate Model 6 using a rich set of controls and fixed effects. The results are shown in Table 2. Each column represents a model with different sets of fixed effects. The coefficient in the first row represents the baseline price sensitivity. The key coefficient of interest is in the second row, the interaction between price and the price variability stock. We find an increase in price sensitivity when users are exposed to greater price variability, conditional on the same number of historical visits and purchases. On average, we find that consumer price sensitivity increases by $\sim 7.6\%$ over the baseline. In Appendix D, we report similar results from robustness specifications with a linear model estimated using OLS.

Our fixed effects estimates in Table 2 control for observed historical user-level search intensity and for time-invariant unobserved user and product heterogeneity. However, we may worry about "strategic" user behavior where users time there visits when price changes are likely to happen. In columns (2) and (3) of Table 2, we control of hour-of-day and day-of-week fixed effects and report similar findings. To some extent, these findings internalize our earlier stylized facts (Section 4.2) that user visitation times are not effectively strategic: users are equally likely to experience a high or low price on each subsequent visit. Nevertheless, there is still a possibility to neglect time-varying unobserved confounds. We use three instrumental variables to further provide conclusive causal evidence.

Table 2: User-level Exposure to Price Variability—Poisson Model with Fixed Effects

Dependent Variable:	Units		
Model:	(1)	(2)	(3)
Variables			
Log price	-1.14***	-1.14***	-1.14***
	(0.058)	(0.058)	(0.058)
Log price x Price variability stock	-0.076***	-0.076***	-0.076***
	(0.007)	(0.007)	(0.007)
Price variability stock	0.133***	0.135***	0.136***
	(0.016)	(0.016)	(0.016)
Log # of prior purchases	-0.356***	-0.354***	-0.354***
	(0.010)	(0.010)	(0.010))
Log # of visits	0.287***	0.285***	0.284***
	(0.016)	(0.016)	(0.016)
Log # of products viewed	0.229***	0.227***	0.226***
	(0.007)	(0.007)	(0.007)
Fixed-effects			
User	Yes	Yes	Yes
Product	Yes	Yes	Yes
Year week	Yes	Yes	Yes
Hour		Yes	Yes
Day of week			Yes
Fit statistics			
Observations	9,452,016	9,452,016	9,452,016
Pseudo R^2	0.210	0.210	0.210
Log-Likelihood	-2,233,555.4	-2,232,939.9	-2,232,631.7

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

The models in Table 2 control for time-varying user-level search and purchase histories. As robustness, here we more flexibly control for the search and purchase histories by creating quintiles and including indicator variables for each quintile in the main model. Table 3 shows the results for our main fixed-effects models. We suppress dummy coefficients and focus on the key coefficients. We find that our results are robust alternative functional forms for the control variables.

Table 3: Robustness Checks for User-level Elasticity Estimates using Flexible Controls

Dependent Variables:	Units Poisson	Log units OLS
Variables		
Log price	-1.16***	-0.042***
	(0.058)	(0.002)
Log price x Price variability stock	-0.073***	-0.0008***
	(0.007)	(0.0002)
Price variability stock	0.268***	0.006***
	(0.016)	(0.0005)
Fixed-effects		
User, Product, Year week		
Fit statistics		
Observations	9,452,016	10,638,420
Pseudo R^2	0.207	-0.239
Log-Likelihood	-2,241,018.0	3,269,995.9

Clustered (User & Product) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*
Controls include indicators for quintiles of historical user purchases, user visits, and product viewed.

6.2 Instrumental Variables

We address concerns of systematic biases in a user's observed price variability stock, A_{it}, by exploiting exogenous price variability that is directly related to A_{it}. These strategies implicitly exploit the variation in the timing of a user's visits to the website. Specifically, the exact time a user visits the platform can be thought of as-good-as-random with respect to prices—this assumption has strong empirical support in the robustness checks we carefully developed in Section 4.2. We first discuss the validity of the instruments and then present the empirical results. We create the following three IVs:

1. *Unseen prices* by the user for the same product in nearby time periods
2. *Price in another state* for the same product in the same time interval
3. *Price of an unseen product* from the same category at the same time

Our first instrument exploits the number of price changes a given user *could have seen*, had she visited at a different time, but did not see. The intuition is fairly 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 A_{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 15 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 15 days, j's price fluctuated independently of these two users' visits. And because of 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 A_{ij} and $A_{i'j}$. However, it does not depend upon the prices not observed, which makes the unseen price variability a valid instrument.

A second instrument relies on geographic price discrimination across states. We build upon the evidence of Aparicio, Metzman, and Rigobon (2021), which reports that online prices often vary across delivery zip codes for the same product and date. 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 A_{it} using the price variability stock 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 the Hausman-style instruments (Hausman, 1996; Nevo, 2001; Berry and Haile, 2014; Adams and Williams, 2019; DellaVigna and Gentzkow, 2019), and (b) while price levels can vary, algorithms often trigger price changes across geographies (Aparicio, Metzman, and Rigobon, 2021).

Finally, we use a third instrument motivated by evidence that price algorithms synchronize price changes across related products (Anderson, Jaimovich, and Simester, 2015; Aparicio, Metzman, and Rigobon, 2021). That is to say, algorithms "bunch" price changes of several products from the same category or brand at close time intervals. For example, all flavors of a particular greek yogurt experience price changes in a short time period. Therefore, we instrument A_{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 their price changes are often synchronized but the price variability in unseen products is uncorrelated to a purchase decision (Ellison and Ellison, 2009).

Table 4 reports the first-stage results for the three IV approaches. Moreover, in all cases the first stage results and F-stats indicate strong instruments.

[10]The instrument is qualitatively similar to the instrumental variables approach in Assad, Clark, Ershov, and Xu (2020) to study the effect of algorithmic pricing on collusion across gas stations. The authors use proportion of brand's stations who have adopted algorithmic pricing, with the intuition that brand-level adoption decisions are independent of local station-level shocks.

Table 4: First stage results for control function regressions

Dependent Variable:	PVS	Log price x PVS	PVS	Log price x PVS	PVS	Log price x PVS
Price Variability Stock: PVS						
Model:	Unseen prices		Other state		Unseen product	
Variables						
Log price	0.076***	-0.170***	0.007***	0.028***	0.004***	-0.002
	(0.006)	(0.018)	(0.001)	(0.004)	(0.002)	(0.006)
IV	0.345***	-0.339***	0.993***	-0.010***	0.946***	-0.024***
	(0.003)	(0.012)	(0.0007)	(0.002)	(0.001)	(0.003)
IV Interaction	-0.009***	0.477***	-0.0005***	0.996***	0.002***	0.963***
	(0.0009)	(0.005)	(0.0001)	(0.0006)	(0.0004)	(0.002)
Log # of prior purchases	0.073***	0.145***	0.0008	0.002	0.002**	0.006**
	(0.004)	(0.007)	(0.0008)	(0.002)	(0.001)	(0.003)
Log # of visits	0.333***	0.689***	0.004**	0.009**	-0.008***	-0.017***
	(0.009)	(0.019)	(0.002)	(0.004)	(0.002)	(0.004)
Log # of products viewed	0.058***	0.136***	0.001*	0.003*	0.010***	0.021***
	(0.003)	(0.007)	(0.0007)	(0.002)	(0.0007)	(0.002)
Fixed-effects						
User, Product, Year week						
Fit statistics						
Observations	10,638,420	10,638,420	3,141,664	3,141,664	2,411,444	2,411,444
F-stat	210.3	188.8	25,926.8	27,990.4	3,294.9	3,364.5
Log-Likelihood	-6,841,824.4	-15,883,227.9	4,219,945.4	1,515,815.7	1,985,809.9	-61,887.0

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

We use the three instrumental variables described above to causally pin down the effect of price variability on price sensitivity. We use two-stage control function (Petrin and Train, 2010) because Model (6) is non-linear. In all models, we instrument for the price variability stock (A_{it}) and its interaction with price ($\log(P_{ijt}) \times A_{it}$). In the first stage, we run two regressions: (a) A_{ij} on the instrument Z_{ij}, exogenous controls (X_{ijt}), and the fixed effects from Eq. 6, and (b) $\log(P_{ijt}) \times A_{it}$ on $\log(P_{ijt}) \times Z_{it}$, X_{ijt}, and the fixed effects. In the second stage, we estimate Eq. 6 by including the residuals from the two first-stage models.[11] Standard errors are bootstrapped and clustered at the user and product levels.

[11]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. See additional discussions in Petrin and Train (2010); Wooldridge (2015); Ebbes, Papies, and van Heerde (2021).

Table 5: User-level IV Model—Two Stage Control Function

Dependent Variable:	Units		
IV:	Unseen prices	Other state	Unseen product
Variables			
Log price	-1.05***	-1.11***	-0.895***
	(0.059)	(0.076)	(0.063)
Log price x Price variability stock	-0.157***	-0.082***	-0.059***
	(0.010)	(0.008)	(0.011)
Price variability stock	0.485***	0.225***	0.499***
	(0.025)	(0.023)	(0.025)
Log # of prior purchases	-0.371***	-0.397***	-0.501***
	(0.010)	(0.018)	(0.021)
Log # of visits	0.189***	0.329***	0.276***
	(0.017)	(0.030)	(0.022)
Log # of products viewed	0.187***	0.205***	0.079***
	(0.008)	(0.014)	(0.009)
First stage residual - 1	-0.591***	-0.281	-0.964***
	(0.028)	(0.209)	(0.119)
First stage residual - 2	0.175***	0.215**	0.248***
	(0.011)	(0.089)	(0.049)
Fixed-effects			
User, Product, Year week			
Fit statistics			
Observations	9,452,016	2,673,491	1,592,645
Pseudo R^2	0.210	0.240	0.285
Log-Likelihood	-2,231,837.6	-626,745.2	-533,005.5

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

The results from the control function approach, shown in Table 5, consistently indicate that price variability exacerbates price sensitivity. Columns (1), (2), and (3) show negative coefficients for the interaction between price and price variability, when the price variability stock (A_{it}) is instrumented using unseen price changes, price changes in a different market, and price changes in related products, respectively. These results provide direct evidence that consumers become more price-sensitive due to heightened algorithms' price variability. Appendix D reports similar results from a linear model estimated using Two Stage Least Squares (2SLS).

7 Online Experiments

Our previous analyses in collaboration with an online retailer indicate that users who are exposed to higher price variability become more price-sensitive. But are those findings generalizable outside that setting? To address this, we design online lab experiments whereby participants are exposed to high vs. low price variability in a controlled environment.

7.1 Design

The experimental design is as follows. We ask participants to simulate purchase decisions, i.e. participants must click how many units (from 0 to 5) they intend to buy in each period. The online shopping simulation lasts 12 periods, it involves a single product (e.g., Nutella), and the price might fluctuate from period to period. Purchase decisions are sequential: participants answer period 1, then period 2, etc. Moreover, they receive a budget at the beginning which is automatically adjusted based on the units that they have bought so far. Importantly, responses are incentive-compatible. Participants receive a bonus payout that depends on the total units bought and total savings, i.e., users that buy more (less) units when the price is low (high), as they would in real life, receive a larger payout.[12]

Participants are randomly assigned to one of two treatment conditions: algorithmic prices and non-algorithmic prices. Price series are simulated based on the *real* data, and therefore the price variation closely resembles what online platforms do, and in particular our industry partner, with respect to algorithmic prices. As mentioned, algorithmic prices fluctuate frequently and in small amounts, whereas non-algorithmic prices are fairly stationary with small infrequent jumps. Finally, the price sequences across conditions have roughly the same average price (but different price variability).[13]

We run three experiments: (a) with MBA students, (b) on Amazon Mechanical Turk, and (c) on Prolific.[14] Our baseline experiment with MBA students covers 139 distinct users (self-reported average age of 29.8 and 68% male), 48% randomly assigned to algorithmic prices, and 52% randomly assigned to non-algorithmic prices. Reassuringly, we find similar results in experiments (b) and (c).

7.2 Price Sensitivity

To test whether algorithmic pricing exacerbates price sensitivity we estimate the following model:

$$\log(Y_{it}) = \beta_0 + \beta_1 \log(P_{it}) + \boldsymbol{\beta_2} \log(P_{it}) \times \text{High PV}_i + \beta_3 \text{High PV}_i + \epsilon_{it} \tag{7}$$

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 whether/how the price elasticity varies with price variability.

The results are presented in Table 6. Consistent with the field findings in Sections 5 and 6, column (1) shows that participants exhibit a more price-elastic demand when exposed to prices with high variability. As per column (2), the estimates are robust to a Poisson model. Additionally, columns (3) to (6) show a very similar pattern of results in the Prolific and MTURK experiments, respectively.

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

[13]For example, four periods under non-algorithmic prices might be (\$5.98, \$5.98, \$5.76, \$5.76); while the same periods under algorithmic prices might be (\$6.01, \$5.88, \$5.63, \$5.91).

[14]To avoid monetary payouts with students, we offered a ceramic coffee mug to the best participants in terms of units bought and savings.

Table 6: Algorithmic Pricing and Price Sensitivity—Online Experiments

	MBA Classrooom		Prolific		MTURK	
Model:	Gaussian	Poisson	Gaussian	Poisson	Gaussian	Poisson
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(Price)$	-0.373***	-0.126***	-0.485***	-0.167***	-0.432***	-0.178***
	(0.076)	(0.017)	(0.072)	(0.022)	(0.092)	(0.034)
$\log(Price)$ × High PV	-0.515***	-0.187***	-0.255**	-0.113***	-0.427***	-0.173***
	(0.114)	(0.033)	(0.104)	(0.034)	(0.129)	(0.050)
High PV	0.859***	0.827***	0.431**	0.496***	0.755***	0.802***
	(0.196)	(0.143)	(0.181)	(0.153)	(0.222)	(0.216)
Constant	1.236***	0.733***	1.409***	0.859***	1.248***	0.818***
	(0.135)	(0.086)	(0.127)	(0.104)	(0.162)	(0.157)
Fit statistics						
Observations	1,656	1,656	3,132	3,132	2,304	2,304
R^2	0.046		0.036		0.042	
Chi2		237.175		185.458		147.570
Log-likelihood	-1461.779	-2618.563	-2600.363	-4671.754	-2015.231	-3496.202

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

7.3 Price Salience

We now revisit the conceptual framework in Section 3 to shed light on a potential underlying behavioral mechanism. We discussed that the effect of algorithmic pricing on price elasticity is theoretically ambiguous. On the one hand, algorithmic pricing may drive attention to prices (thus, greater price sensitivity); on the other hand, it may "jam" the notion of good/bad deals (thus, lower price sensitivity).

After the 12-period simulated shopping trip, we show participants a screen with a different product (either Oreos or Godiva) for 5 seconds. The screen includes the standard product image, product description, and price. We then ask participants to recall the price and size of that product. If algorithmic pricing makes prices more salient, then a larger proportion of users in that treatment condition will be able to better recall the price of Oreos (or Godiva). (Conversely, if instead leads to signal-jamming, users should be less able to recall the price.) We *operationalize salience as recall*, following abundant tradition in behavioral sciences, economics, and marketing. See, for example, Alba and Chattopadhyay (1986); Kissler, Herbert, Peyk, and Junghofer (2007); Finkelstein (2009); Kroft, Lange, and Notowidigdo (2013); Gaspelin, Leonard, and Luck (2015). To illustrate, Alba and Chattopadhyay (1986) articulate this clearly when they write: "*[...] exposure to a brand increases its salience, thereby increasing the ability of a consumer to recall it. 'Salience,' as used here, refers to the prominence or 'level of activation' of a brand in memory. 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.*"

Therefore, we test whether the proportion of correct responses is higher in the algorithmic pricing condition. We first classify a participant with a correct response if their answer was within 10% of the correct price. More formally, consider a participant i who answers X_i; we define recall

R_i as follows:

$$R_i = \begin{cases} 1, & \text{if} \quad |X_i - P^*| \le \text{Price} \times 10\% \\ 0, & \text{otherwise} \end{cases}$$

where P^* is the correct price of Oreos (or Godiva). Therefore, the proportion of correct participants in each treatment condition is: $p_{\text{Algo}} = \frac{1}{N_{\text{Algo}}} \sum_i R_i$ for algorithmic prices and $p_{\text{Non-Algo}} = \frac{1}{N_{\text{Non-Algo}}} \sum_i R_i$ for non-algorithmic prices.

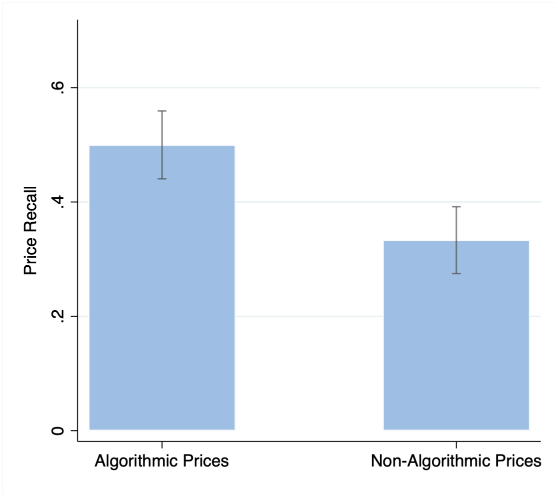


Figure 12: Algorithmic Pricing and Price Salience

We find evidence that algorithmic pricing makes price more salient. A visual summary is depicted in Figure 12: the fraction of correct responses is roughly 50% 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 the following model:

$$\text{Recall}_i = \beta_0 + \beta_1 \text{High PV}_i + \epsilon_i \tag{8}$$

where Recall_i is an indicator variable that takes value 1 if user i correctly recalled the price (or 0 otherwise); and High PV_i is the indicator variable defined before. We also re-estimate Eq. (8) with the log absolute recall error.

Table 7 shows that participants exposed to algorithmic prices are more likely to recall the price correctly and have a lower recall error, as per columns (1) and (2), respectively. We find similar results in Prolific experiments (columns (3) and (4)) and MTURK experiments (columns (6) and (6)), controlling for time spent hovering each object in the screen with the mouse. While not a core objective of the design, for completeness we also asked participants to recall the package size (Oreos) or count of chocolates (Godiva's). As expected, participants in the condition of interest experience directionally worse recall (Appendix E).

Table 7: Algorithmic Pricing and Price Recall—Online Experiments

	MBA Classrooom		Prolific		MTURK	
	(1)	(2)	(3)	(4)	(5)	(6)
High-PV	0.167**	-0.120	0.105**	-0.158*	0.105*	-0.230**
	(0.084)	(0.191)	(0.051)	(0.094)	(0.063)	(0.115)
Fit statistics						
Observations	138	138	261	261	193	193
R^2	0.028	0.003	0.125	0.130	0.126	0.142
Log-likelihood	-96.392	-210.534	-129.966	-292.320	-109.350	-225.357

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

In summary, the evidence supports price salience as the process through which high price variability increases price sensitivity. We emphasize that the existence of price salience does not preclude the role of other behavioral phenomena. We hope these results spark further debate about the interaction of algorithmic pricing and consumer behavior.

7.4 Eye-Tracking: Additional Evidence

Salience may also be thought of as relatively more attention. We obtain another set of evidence which 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 an 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, Krishna, and Elder, 2015).[15]

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

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

the following model:

$$\tau_{it} = \beta_0 + \beta_1 \text{Price Displayed}_i + \delta_t + \gamma_s + \epsilon_{it} \tag{9}$$

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.

Table 8: 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 8 shows the results. When the advertisements on the 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, Shiv, and Knutson (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.

8 General Discussion

Artificial Intelligence automates human decisions. A form of AI for pricing is algorithmic pricing: a manager gives a machine a set of instructions—a formula—to automate price setting. As more businesses welcome AI (and vendors offer AI-based solutions at low monthly fees for small enterprises), our knowledge about the human/machine intersection will keep growing. Our work studies an intersection that has been relatively underdeveloped: algorithmic pricing and consumers' price sensitivity.

Industry practitioners often express concerns about "lagging behind" in the race of adopting state-of-the-art pricing technology. To some extent, those concerns make sense because there is extensive evidence that firms are better off using algorithmic pricing (Aparicio and Misra, 2022). Intuitively, it allows businesses to react in real-time to shocks, to learn demand signals, to react to competitor prices, and to price discriminate. But what if there is a side effect to algorithmic pricing? What if consumers react in an unforeseeable way which "eats" part of those gains? This is a critical insight to, for example, a growing literature on demand learning (Misra, Schwartz, and Abernethy, 2019). Algorithmic pricing is extremely useful to learn the demand—However, our findings show that we shall also consider how those demand primitives are actually shifting precisely as a consequence of exposure to algorithmic pricing.

In collaboration with an online grocery platform in the U.S., we find that consumers' *price sensitivity exacerbates* as they get exposure to higher price variability. We confirmed this evidence in various online lab experiments (MBA classroom, Prolific, MTURK). Additionally, the experiments allowed us to identify that a key underlying mechanism is *price salience*. That is, higher price variability makes prices more salient.

Algorithmic pricing is becoming increasingly observed in many markets and, presumably, is here to stay. Rather than challenge the popularity of AI pricing, our findings encourage scholars to keep contributing to the complexities of the human/machine intersection. To conclude, below we discuss several implications and areas of future research.

Personalization. Which businesses want their customers to become more price-sensitive? The answer is probably very few. Perhaps price aggregator platforms or everyday low prices (EDLP) retailers might stand to benefit, but in general, businesses would like to avoid this side effect. How to account for this demand rotation is not trivial and, to our knowledge, it remains overlooked. In theory, it could be an "input" to perfect the technology: a firm could *personalize algorithmic pricing* to mitigate behavioral reactions. For example, it may be optimal to coarse the price grid based on each users' past price exposure in order to attenuate (unnecessary) price variability exposure. Said differently, prices may be personalized depending on the exposure to, and sensitivity to, price variability.[16]

Haphazard Online Visits. Online groceries is an ideal setting to explore effects of algorithmic pricing because it is a recurring environment (vs. one-off purchase), i.e. consumers enter the online store to buy multiple products relatively frequent. This is useful empirically—Consumers that browse the same products in nearby timestamps get exposed to different degrees of price variability over time. These haphazard timings in customers' visits in online/mobile platforms can be utilized for identification when ideal experiments are not available (Donnelly, Ruiz, Blei, and Athey, 2021; Borusyak and Hull, 2020).

Misspecified Demand. Most explore-and-exploit algorithms consider (realistic) settings where the demand function is unknown to the firm (Misra, Schwartz, and Abernethy, 2019; Cohen, Lobel, and Paes Leme, 2020; Wang, Chen, and Simchi-Levi, 2021). But what if those pricing experiments modify the demand primitives? Indeed, our work shows that customers exposed to greater price variability become more price-sensitive. These have critical implications for firms that are tirelessly exploring the price grid to seek the optimal price. precisely as a consequence of those experiments, the "optimal" prices are no longer optimal, at least for those users.

Salience. The online lab experiments confirm that higher price variability exacerbates price sensitivity and, importantly, reveal that a key mechanism through which this happens is *price salience*. The secondary eye-tracking data obtained from a technology company—showing

[16]To illustrate: Imagine that p^a_{i,t_1} is the price seen by user a for product i at time t_1. Imagine that the algorithm outputs $\tilde{p}_{i,t_2}$ as the "optimal" price for time t_2. However, the firm may want to set $p^a_{i,t_2} = p_{i,t_1}$ for user a (p_{i,t_1} and $\tilde{p}_{i,t_2}$ are very close) but $p^b_{i,t_2} = \tilde{p}_{i,t_2}$ for user b.

that view time is higher for advertisements in digital screens containing prices—provides complementary evidence about the behavioral role of price salience. Having said that, we are mindful that the existence of price salience does not preclude other mechanisms to operate simultaneously. Exploring the intersection with other behavioral phenomena such as price knowledge (Dickson and Sawyer, 1990b), price fairness (Xia, Monroe, and Cox, 2004; Anderson and Simester, 2008; Allender, Liaukonyte, Nasser, and Richards, 2021), acceptability (Lichtenstein, Bloch, and Black, 1988), fatigue (Ursu, Zhang, and Honka, 2022), wholesale pricing and fairness (Rotemberg, 2005; Katok, Olsen, and Pavlov, 2014), fairness to machine algorithms (Lee, 2018), limited memory (Chen, Iyer, and Pazgal, 2010), or price cues (Lourenço, Gijsbrechts, and Paap, 2015), is a promising avenue of future research.

Behavioral Automation. While AI automates managerial decisions, businesses cannot neglect the behavioral input to algorithms. This is not trivial, because it often involves different teams within an organization, whose coordination is subject to frictions, biases, budgets, and incentives (Hortaçsu, Natan, Parsley, Schwieg, and Williams, 2021). Ultimately, methodological improvements in the back-end (e.g., speed of optimization, high-dimensional inputs, price matching) are not sufficient in isolation; their connection to front-end user experiences should be factored in.

Questions Going Forward

Going forward, it would be valuable to differentiate short-term effects from long-term implications. Algorithmic pricing technology is fairly new and even specialized AI vendors are continually experimenting and updating their models. Studying the long-term impact of this new-age pricing technology on consumer behavior and market structure will help inform both business strategies and regulatory policies. Another important dimension, beyond the scope of this paper, is competition. Firms are not using price algorithms in isolation and a key input to these algorithms is competitor prices. If algorithmic pricing heightens price sensitivity, what does it mean for collusive price algorithms? Can a firm exploit to its own advantage that its rival's customers are now more price-sensitive? Characterizing the equilibrium effects between consumers and firms when multiple players in the market adopt algorithmic pricing, and when customers behaviorally respond to those algorithms, is an interesting avenue to pursue.

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