Nonlinear Pricing Complexity: Consumer Errors and Firm Profits

Evidence from a "uniquely frustrating" experiment[*]

Joshua Deutschmann, Jeffrey D. Michler, Emilia Tjernström

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Latest version here.

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1 Introduction

The trade-offs between the costs of information processing and the returns to better information have never been starker. Consumers today participate in large number of markets and have access to enormous amounts of information. To make a "full-information rational decision" requires processing signals regarding quality and price across a range of markets, as well as assessing the informativeness of the signals themselves. Alongside a growing literature documenting that observed behaviors do not always reflect people's preferences, economists have developed increasingly general models of decision-making to explain this phenomenon. Broadly writ, these models try to explain the gap between the information that consumers theoretically have access to and that which they act upon.

At the same time, firms have access to increasingly detailed data on their consumers. While some consumer advocacy groups worry that the advent of big data and sophisticated algorithms will move markets closer to perfect price discrimination, consumers may dislike overly fine-tuned zone pricing, perceiving them as unfair (as discussed in Dellavigna and Gentzkow 2019 and Ater and Rigbi 2018). Of course, personalized pricing is not the only way that firms can price discriminate. A common alternative approach to screening is to offer non-linear prices, such as quantity discounts and differential pricing for bundles of goods. One of the key benefits of bundling—a form of pricing where combinations of goods are priced differently than the separate components—is that it reduces firm uncertainty about consumer valuations. As Bakos and Brynjolfson (1999) note, it is much easier to predict consumer valuations for a bundle of many unrelated goods than it is to predict their valuations for these same individual goods sold separately.

Bundling is the focus of our study. One benefit to the firm of this form of price discrimination is that consumers tend to be less concerned with their fairness than in the case of narrowly targeted prices. However, many nonlinear pricing problems are complex to solve; most lack analytical solutions—especially with settings with many goods. For example, the computational complexity of price-setting for mixed bundling (offering a complete bundle of all products, as well as every possible subset) increases exponentially with the total number of goods produced.

Computational complexity is part of the motivation in Chu, Leslie and Sorensen (2011); henceforth CLS11. They introduce bundle-sized pricing (BSP) as a "simple" alternative to mixed bundling (MB) that nonetheless does almost as well—in their simulated experiments, BSP obtains on average 98% of the profits of MB but with a much simpler price schedule. CLS11 motivates their search for a simpler price menu by granting that it may be hard for firms to set a large number of prices. For a firm with ten products, the profit-maximizing MB solution would require the firm to set 1,023 prices. But, "if that is not feasible (likely), then offering all products only as a single package may be more profitable than offering them individually."

We turn this around and assume that firms have perfect information and unlimited computing capacity, and instead evaluate the implications of practical constraints on the consumer side. How does the complexity of such pricing schemes affect consumer behavior? If firms incur substantial costs while solving for the optimal price, it seems equally plausible that consumers may respond in unexpected ways to long, complex price menus. We explore this question by experimentally studying consumer behavior in a context where we have relatively clean theoretical predictions for optimal firm behavior—and where these predictions may change in predictable ways if decision-makers depart from "full-information rational choice" models.

Our study participants make a large number of choices between bundles of goods of varying sizes under four different pricing mechanisms: component pricing (CP), MB, BSP, and pure bundling (PB). Pilot data reveals that consumers obtain a smaller share of the achievable surplus as the number of goods increases, but only for mixed bundling and component pricing. Pure bundling and BSP are relatively immune to the number of goods that consumer have to choose from.

Our work fits broadly into the growing body of research that addresses the issues that may arise when we rely on revealed behavior to infer preferences. Caplin (2016) motivates his review of the research on attention modeling by noting the large gap between the information that consumers have access to and the information that they act upon. Illustrations of this gap abound, and come from a wide range of fields. For example, Chetty et al. (2009) note that consumers often neglect to respond fully to sales taxes when these are not salient. Bhargava et al. (2017) show that a majority of employees in their sample choose clearly dominated health insurance plans, at substantial economic losses. Additionally, several innovative laboratory experiments have demonstrated evidence of limited attention, including Gabaix et al. (2006), Caplin and Martin (2017), and Dean and Neligh (2019).

Within this broad umbrella of work, researchers approach departures from the full-information rational model in different ways. An important distinction is whether consumers are boundedly rational or if consumers *de facto* make rational decisions—but base these decisions on incomplete information. The former approach often highlights the ways in firms can exploit consumers' overconfidence, sub-optimal searching, excess inertia, etc.. The "rational inattention" framework instead focuses on the fact that complete information may be costly to obtain. In most markets, a consumer has to spend time and effort acquiring information. The costs of obtaining the additional information, or of paying attention to it, may be higher than the observing economist assumes. This is especially true when the returns to extra effort are unknown.

In recent experimental work, Caplin et al. (2018) show that there exists a clear analogy between attention costs in consumer choice and production costs for competitive firms' supply decisions. Using an experiment designed to recover attention costs from choice data, they show that consumer welfare net of attention costs can be measured in a way that is analogous to firm profits. By assessing the trade-offs between reward level and task complexity, they recover attention costs within their framework and demonstrate that the behavioral data satisfy tests for the existence of a rationalizing cost function.

In this study, we will not attempt to disentangle whether or our experimental participants are rational or boundedly rational. We instead focus on a specific setting within which consumer departures from "full-information rational choice" may affect optimal firm behavior. The benefit of studying departures from full-information rational consumers in the lab is that we can study consumer and producer surplus in a single setting. The experimental setting also allows us to compare firm profits to the theoretical maximum. By comparing firm profits under "realized" (experimental) demand to the theoretical predictions, we can test whether the pricing mechanisms that maximize profits given the assumptions commonly assumed in theoretical applications also maximize profit under realized demand.

2 A "uniquely frustrating" experiment

To examine consumer choice within our nonlinear pricing context, we have experimental multi-product monopolist firms that set prices optimally based on known distributions of consumer valuations. In the experiment, participants receive valuations for several different goods. Their valuations are drawn based on draws from the distributions that the firm used to set prices. Consumers choose from bundles of goods of varying sizes under four different pricing mechanisms: component pricing (CP), mixed bundling (MB), bundle-sized pricing (BSP) and pure bundling (PB). We compare participants' consumer surplus to the maximum achievable surplus—i.e., that obtained by a rational consumer whose cost of considering the full choice set is zero.

Just as we can compare consumers' attained surplus to the theoretical optimum, the experimental setting allows us to compare firm profits to the theoretical maximum. We examine whether the observed consumer behavior has implications for the firm's optimal choice of pricing mechanism. Theory provides clear predictions for the relative profitability of the different pricing schemes under known consumer demand. We test whether the complexity of nonlinear prices affects consumers' ability to find the optimal bundle, and whether departures from "full-information rational choice" changes the profitability rankings of these pricing schemes.

In addition to showing that BSP is a practical alternative to MB, CLS11 also examine a wide range of demand and cost primitives in simulated experiments. This allows them to evaluate the relative profitability of different pricing schemes under a range of scenarios. The parameters that they examine include the number of goods (from 2 to 5), the nature of correlation between consumers' tastes, the amount of demand asymmetry, and the cost structure facing the firm. These characteristics had also been studied in the prior literature as factors that influence the relative profitability of PB over CP.

We will focus on two of these parameters: the number of goods and demand asymmetry. In the theoretical literature, it is clear that MB should dominate the other pricing schemes—they are all special cases of MB. For the other pricing schemes, the rankings change depending on the context. For example, in the absence of consumer attention costs we would expect bundling-type prices to be more profitable when the number of goods increases. The intuition behind this is that inducing consumers to buy larger bundles reduces the heterogeneity in consumer valuations for the products. With less heterogeneity, the firm is able to extract more surplus. CLS11 focus most of their comparisons on CP vs BSP (since MB should dominate all the other options). Once we examine consumers who have a limited attention span, this may or may not hold.

Similarly, demand asymmetry has clear predictions for the rankings of CP and PB relative to MB. Specifically, conventional wisdom has it that demand asymmetry should reduce the profitability of bundling-type prices relative to CP. In CLS11, it turns out that the comparison between BSP and CP is non-monotonic: increasing demand asymmetry initially decreases then increases the profits of BSP relative to CP. Again, it is unclear what consumer mistakes or rational inattention will imply for these rankings.

Table 1: Demand distributions under symmetric and asymmetric demand

Number of goods	**Symmetric**		**Asymmetric**	
	Color name	Demand	Color name	Demand
≥ 2	Brick	U[0,50]	Dark Maroon	U[0,10]
	Denim	U[0,60]	Navy Bluetiful	U[0,100]
≥ 3	Fern	U[0,55]	Middle Green	U[0,55]
≥ 5	Violet	U[0,60]	Royal Purple	U[0,100]
	Orange	U[0,50]	Mango Tango	U[0,10]
≥ 7	Pine	U[0,60]	Tropical Rain	U[0,100]
	Golden	U[0,50]	Dandelion Yellow	U[0,10]
≥ 9	Sky	U[0,60]	Turquoise Blue	U[0,100]
	Peach	U[0,50]	Desert Sand	U[0,10]

2.1 Experimental design

We pair our experimental participants with fictional price-setting multi-product firms. In each round t, the consumer interacts with a different firm. Each firm offers a fixed set of goods, J_t, which contains k_t different goods, with $k_t \in \{2, 3, 5, 7, 9\}$. The goods are denoted by colors and a given firm offers a subset of the goods presented in Table 1.

Some of the firms face symmetric demand, while others face asymmetric demand. Table 1 also shows the distributions of demand for each type of good under symmetric and asymmetric demand.

Price-setting firm

Each "firm" prices the goods that they sell under a specific type of pricing strategy, based on perfect knowledge of the distributions of demand shown in Table 1.

Pricing strategies

We focus on four pricing strategies that are common in the literature on multi-product pricing: component pricing (CP), pure bundling (PB), mixed bundling (MB), and bundle-size pricing (BSP). Denote the set of pricing schemes by $\Omega = \{\mathrm{PB}, \mathrm{BSP}, \mathrm{CP}, \mathrm{MB}\}$.

Consumer demand

The firms profit-maximize given the relevant consumer demand that they face. We denote the profit-maximizing price of a bundle b by $P_{b\omega}$, with $\omega \in \Omega$. [1]

Valuations

We assign our experimental participants private valuations for each of the 18 different goods. We randomly draw the valuations from the demand distributions in Table 1 and denote each good by a color. Each color comes in two different versions, labeled with names inspired by Crayola crayons that look virtually identical to non-experts. The difference between a given consumer's valuation for Brick and Maroon is that her valuation for Brick is drawn from $U[0, 50]$ while her valuation for Maroon is drawn from $U[0, 10]$. These draws are independent, so a consumer could receive a high valuation for Brick and a low valuation for Maroon, or any such combination. Figure 1 shows how experiments learn their valuations; these valuations remain constant across all rounds.

[1]For CP and PB, the profit-maximization procedure is relatively trivial. In contrast, the pricing problem for MB and BSP when the number of goods exceeds 2 has no analytical solutions and therefore must be solved with simulation. Appendix XXX provides more detail on these simulations.

Choice sets

Let K_k denote the set of possible goods-combinations of size k. For $k = 4$, for example, we could theoretically present consumers with $\binom{9}{4} = 126$ different combinations of goods. To increase comparability across as well as within participants, we constrain this set to those listed in Table 1. In other words, the choice set that consumers face when $k = 2$ under symmetric demand is $K_2^s = \{\text{Brick}, \text{Denim}\}$. Similarly, under asymmetric demand consumers face $K_2^a = \{\text{Maroon}, \text{Navy}\}$.

Payoffs

Let v_{ij} denote how much Mrs. i values good j. We do not allow for any correlations in consumer valuations of goods, so her gross payoff for bundle b can be written as

$$G(v_{ib}, P_{b\omega}) = \sum_{j \in b} v_{ij} - P_{b\omega}$$

We call it gross payoffs due to the fact that we are not accounting for the cost of making the decision, which a growing literature on rational inattention has shown to be important.

Game play

During the game, each consumer faces each type of pricing mechanism for all the different goods shown in Table 1.

2.2 Drop-Out Experiment

In order to measure participants' preferences to avoid certain complex pricing schemes, we conduct an additional drop-out experiment at the end of the game. After completing all scheduled rounds, in which participants face all pricing schemes for all values of k_t, consumers are shown a "bonus round" with a randomly drawn pricing scheme and value of k_t. They are informed that they can choose to skip this round, and receive the payout they've been allocated based on their performance in the game, or they can choose to play the bonus round, in which case their payoff would be based solely on that round. We measure drop-out as the choice to skip the bonus round.

Color	Value
Red	23
Blue	10
Green	43
Purple	58
Orange	2
Maroon	5
Yellow	30
Grey	13
Lavender	36

Figure 1: Screenshot of how we present valuations to the experimental participants

3 Empirical analysis

3.1 Variable definitions

In order to compare consumers' payoffs to the theoretical optimum[2], we define some additional variables. First, we define G_{it}^{max} as the (gross) payoff from choosing b^*, i.e. the bundle that maximizes $\sum_{j \in b} v_{ij} - P_{b\omega}$ conditional on the set of bundles available in round t.

We then define Σ_{it} as the difference between Mrs. i's actual payoff in round t and the maximum theoretical payoff, divided by the theoretical maximum:

$$\Sigma_{it} = \begin{cases} \frac{G_{it}^{max} - G_{it}^{actual}}{G_{it}^{max}} & \text{if } G_{it}^{max} > 0 \\ 0 & \text{if } G_{it}^{max} = 0 \end{cases} \tag{1}$$

To address the fact that Σ_{it} equals zero both when Mrs. i chooses a bundle that yields as gross payoff of zero when $G_{it}^{max} > 0$ and when $G_{it}^{max} = 0$, we include an indicator variable in all our regressions that takes a value of one when $G_{it}^{max} = 0$.

We can similarly define the deviations in firm profits from the profits that would

[2] I.e., that attained by a fully rational agent operating in a full-information environment, and who can costlessly process all the information available to her.

obtain if consumers chose the rational payoff-maximizing bundle. First, since that marginal costs are zero, note that $\pi_t^* = \sum_i P_{b^*\omega_t}$. In words, the firm's theoretical profits are simply the price of the payoff-maximizing bundle b^* summed over all participants.

The actual profits, π_t^{actual} obtained by the firm in round t selling the set of goods J_t under pricing scheme ω is simply the sum of the price of the chosen bundles across experimental participants. We can therefore define the difference between these profits and the theoretical profits as

$$\Delta_{it} = \begin{cases} \frac{\pi_{it}^* - \pi_{it}^{\text{actual}}}{\pi_{it}^*} & \text{if } \pi_{it}^* > 0 \\ 0 & \text{if } \pi_{it}^* = 0 \end{cases} \tag{2}$$

3.2 Regression specifications

3.2.1 Consumer behavior and welfare

$$Y_{i,t} = \alpha + \sum_{\underline{b} \in \mathcal{B} \setminus \text{PB}} \beta_{\underline{b}} 1(b_{i,t} = \underline{b}) + \beta_2 N_{it} + \sum_{\underline{b} \in \mathcal{B} \setminus \text{PB}} \delta_{\underline{b}} N_{it} 1(b_{i,t} = \underline{b}) + \gamma_i + \lambda_t + \epsilon_{it} \tag{3}$$

3.2.2 Firm profits

The specification for firm profits is very similar to that for the consumer welfare. The main difference is the dependent variable, where firm's profit performance (ratio of profit obtained to max profit) is the dependent variable for the firm profit specification.

Note that the firm profit maximum choice is not necessarily the same as the consumer welfare maximum choice.

$$\pi_{i,t} = \alpha + \sum_{\underline{b} \in \mathcal{B} \setminus \text{PB}} \beta_{\underline{b}} 1(b_{i,t} = \underline{b}) + \beta_2 C_{it} + \sum_{\underline{b} \in \mathcal{B} \setminus \text{PB}} \delta_{\underline{b}} Cit 1(b_{i,t} = \underline{b}) + \gamma_i + \lambda_t + \epsilon_{it} \tag{4}$$

3.2.3 Probability of Dropping Out

This regression is used to examine whether participants are more likely to drop out under more complex pricing schemes, and how experimental settings affect the probability of dropping out.

$$D_{i,t} = \alpha + \sum_{\underline{b}\in\mathcal{B}\setminus\text{PB}} \beta_{\underline{b}} 1(b_{i,t} = \underline{b}) + \beta_2 N_{it} + \beta_3 M_{it} + \sum_{\underline{b}\in\mathcal{B}\setminus\text{PB}} \delta_{\underline{b}} N_{it} 1(b_{i,t} = \underline{b}) + \sum_{\underline{b}\in\mathcal{B}\setminus\text{PB}} \theta_{\underline{b}} M_{it} 1(b_{i,t} = \underline{b})$$
$$+ \rho N_{it} M_{it} + \sum_{\underline{b}\in\mathcal{B}\setminus\text{PB}} \mu_{\underline{b}} N_{it} M_{it} 1(b_{i,t} = \underline{b}) + \gamma_i + \lambda_t + \epsilon_{it} \quad (5)$$

with
D_{it}: equal to one if choosing the one dollar treatment in round t (i.e., participant i chooses to drop out in round t)
M_{it}: equal to one if the maximum attainable surplus is negative

An additional variable that can be included is the maximum attainable surplus, as I expect the participants are less likely to drop out if the maximum attainable surplus is high, which makes dropping out an obvious bad choice. Due to parsimony I do not include it there.

4 Pilot results

The following results are from a pilot study run in 2018, which was unfortunately run with incomplete price simulations. Figure 2 shows results from the following regression and Figure 3 shows the effect of complexity on the probability that the consumer drops out, here measured as purchasing nothing when a positive surplus was available:

$$Y_{it} = \alpha + \beta_1 B_{it} + \beta_2 N_{it} + \beta_3 (B_{it} \times N_{it}) + \beta_4 G_{it} + \gamma_i + \lambda_t + \epsilon_{it}$$

where B_{it} is a dummy variable for “complex” price schemes, N_{it} denotes the number of goods, G_{it} represents other round-level game characteristics and γ_i is participant fixed effects.

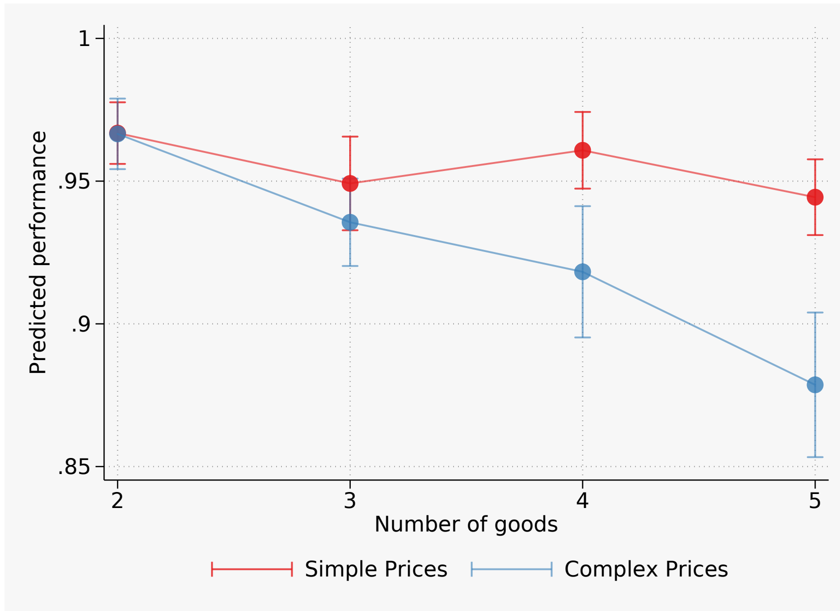

Figure 2: The effect of complexity on consumer surplus, by the number of goods

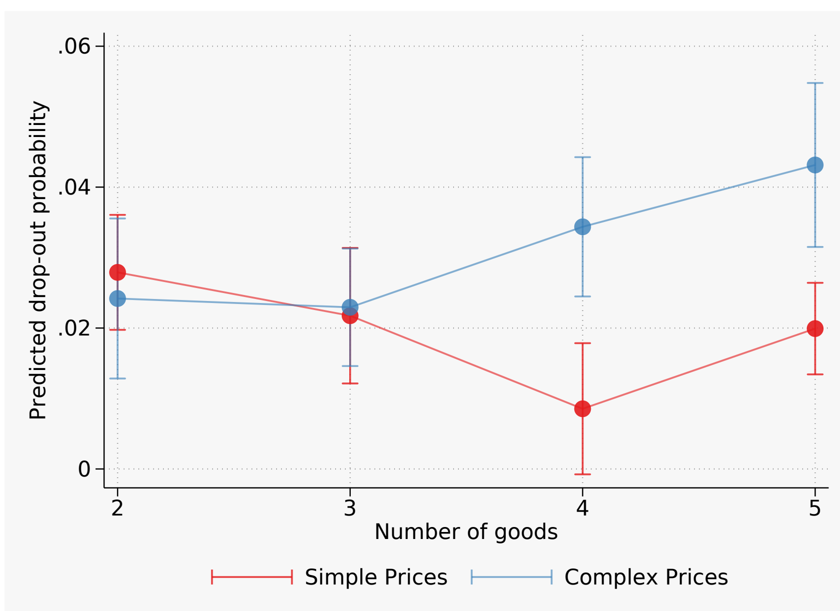

Figure 3: The effect of complexity on the probability of consumer dropout