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Consumer's response to price distribution and σ-overload under time allocation

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ABSTRACT

It has been recently suggested that both the number of options considered by consumers and their satisfaction when shopping respond to changes in the mean and spread of market prices. A structured analysis of those responses is provided in this paper. A new adverse effect related with consumer's welfare is presented here, namely a consumer that searches exhaustively among all market options – called maximizer – experiences welfare loss when the dispersion of prices is too high. In fact, her welfare exhibits an inverted-U shape with respect to the standard deviation σ of prices so that an increase in price spread produces more welfare for small values of σ but it has a negative effect for larger values of σ. This new phenomenon is termed σ-overload. It is also shown that a consumer that is content with shopping from a reduced sample of options – a satisficer – avoids σ-overload by adapting her search behavior to the increase in spread. A quantitative assessment of consumer's behavior and welfare with respect to changes in the mean and dispersion of prices under different scenarios is also provided.

1. Introduction

A classical problem in economic theory consists of determining a consumer's demand for a product whose price is given, according to a rational assessment of welfare which in turn is produced from consumption of the product. An alternative viewpoint focuses on a rational assessment of the welfare produced by different uses of time, so that a consumer's decision when shopping for a product – whose distribution of prices is given – is obtained as a by-product of her rational allocation of time among alternative uses.

Specifically, a consumer is considered in this paper who goes shopping for some consumption good. There are a number of shops or sites offering the good and each one sets the price for its own version of the product. When shopping, the consumer faces a cost in terms of time, namely visiting each shop to inspect price and quality of the product version. Shopping cost is exogenously given. Shopping time has an opportunity cost, since time can be spent in other alternative and desirable uses. Two alternative uses of time are considered in this paper, leisure time and working time. The consumer searches the cheapest price among the valid versions of the product, so that there is a trade-off between visiting an additional shop – so

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that a better deal may be found – and spending some more time in other rewarding uses. Market prices of the product are assumed to follow a given probability distribution. Thus, visiting a number of n shops can be understood as taking a sample of n prices from the underlying price distribution. The main goal of the paper is to analyze the consumer's shopping behavior and welfare in response to a change in the basic characteristics of the price distribution, namely its mean and dispersion.

Following Álvarez et al. [1], a consumer who visits all available shops is called a maximizer, whereas a consumer who visits only an optimal number of the existing shops is called a satisficer. These two types of consumers are possible avatars of the maximizer and satisficer decision makers considered by social psychologists (see [2]). Within the framework of this paper, given a price distribution and a market of size N, i.e. a sample of N prices/shops, a maximizer visits all the N shops to make her decision whereas a satisficer visits a subsample of size n, $n < N$, which is further selected optimally in terms of her welfare.

It was suggested in [1] that, for any number of shops, both a maximizer and a satisficer with constant unit shopping cost typically lose welfare when the average price increases whereas they gain welfare as price dispersion increases. Also, the number of shops visited by a satisficer should decrease when the price mean increases whereas it should increase when price dispersion increases. Assuming a more general structure for shopping costs, a systematic numerical study of these qualitative responses is addressed in this paper. In particular, it is shown that the number of shops visited by a satisficer can be consistently estimated from the mean and dispersion of prices. This quantitative analysis may produce useful information, say for a shop manager that should take into account the reaction of potential shoppers when setting the price for its product.

The celebrated paradox of choice is a striking phenomenon originally described by social psychologists. It implies that a large number of shopping options will have a negative impact on consumer's welfare assuming that he is a maximizer. The choice overload effect has been reported empirically in a number of studies triggered by Iyengar and Lepper [3] and Schwartz [4]. Its general validity remains controversial [5], however, and current research revolves around finding pre-conditions for choice overload. The paradox of choice has been numerically explained within the time allocation framework in this paper in [6]. Specifically, for a typical class of maximizers, when the number N of shops in the market becomes too large their welfare decreases.

As explained above, the analysis in this paper concerns the effect on welfare which is due to variations in the mean and dispersion of prices/shops rather than provoked by an increase in the number of shops N—considered fixed here. A main result of the paper unveils a new adverse effect on consumer's welfare which we call σ-overload. Under the natural assumption that the shopping cost correlates positively with the standard deviation σ of prices, it is shown that a maximizer's welfare has an inverted-U shape with respect to σ. Thus, a mean-preserving spread of a sample of N prices produces a decrease in her welfare if the spread is too large. Even though some dispersion may be beneficial, too much dispersion hurts. However, under the same conditions, the welfare response of a satisficer does not exhibit σ-overload. Rather, a satisficer is capable to adapt her shopping behavior to any price spread in a way that she never suffers a loss of welfare.

The paper is organized as follows. In Section 2 the general features of the time allocation model are introduced together with the description of the two consumer profiles considered in the paper. In Section 3 specifics are explained about model parameters, shopping cost, consumer's preferences on time use, and the role of price distribution. In Section 4, the results obtained for the maximizer and satisficer problems are discussed in a benchmark case (namely, non-constant unit cost and prices normally distributed). Secondary variations of the benchmark case (i.e. constant unit cost, prices uniformly distributed) as well as further estimation results are presented in an Appendix. It is shown therein how the effect of σ-overload remains when the price distribution changes but not when unit costs are constant.

2. Theory: consumer's time allocation and price distribution

A consumer decides how to spend her total available time (T) in three different rival uses of time: shopping time to visit each shop and check its version of a wanted product, working time to get additional income, and free time devoted to leisure, consumption of goods or some activity other than shopping or working. The consumer must then fulfill the time constraints

$$T_s + T_f + T_w = T, \quad T_s, T_f, T_w \geq 0, \tag{1}$$

where T_s is shopping time, T_w is working time, and T_f is free time.

Each shop in the market sets one price for its version of the product sought by the consumer. Market prices are obtained as a random sample of size N from a given price distribution $\mathcal{F}$, so that N gives the total number of shops in the market or just the market size. The mean and standard deviation of $\mathcal{F}$ are denoted by μ and σ, respectively.

Given the shape of the price distribution $\mathcal{F}$ and a random sample of n prices, consumer's total expenditure G is bounded from below by the best expected deal, in turn determined by n and the distributional parameters μ and σ, $G = G(n, \mu, \sigma)$. Thus, when n shops are visited, the consumer's decision is subject to the budget constraint

$$G(n, \mu, \sigma) \leq wT_w + V, \tag{2}$$

where w is the wage rate per unit of working time (T_w), and V is non-working income or savings. In words, the consumer's expenditure cannot exceed her income (right hand side in (2)), the latter being implicitly determined by her allocation of time. In this paper μ and σ will vary to evaluate the consumer's response accordingly.

Since the best deal improves as more shops are visited, the consumer has an incentive to spend more time shopping. However, visiting n shops requires a minimum shopping time $\tau(n, \mu, \sigma)$. Thus the consumer must fulfill the time constraint

$$T_s \geq \tau(n, \mu, \sigma). \tag{3}$$

The right hand side of (3) can be interpreted as a shopping time floor. The notation emphasizes the fact that the time floor may depend on the distributional parameters (μ, σ). Specifically, it can be assumed that τ increases with respect to both μ and σ. The rationale behind these assumptions is rather intuitive. Regarding μ, it seems natural that the higher the average price, the more cautious the consumer is when inspecting the available options, which takes more shopping time. On the other hand, when σ is large so that market prices are very dispersed, the consumer will generally be more cautious as well to learn why prices differ, thus increasing her shopping time floor. These ideas are incorporated into the model by translating cautionary inspection into required shopping-time. Additionally, these distributional effects are decoupled from the pure scale effect (number of sites visited) by assuming

$$\tau(n, \mu, \sigma) = c(\mu, \sigma)n, \tag{4}$$

so that the marginal shopping cost $c(\mu, \sigma) > 0$ is the inspection time per visited shop.

Assuming a standard rational behavior, the consumer seeks to maximize her welfare. Since this depends on the way she decides to use her time, consumer's welfare can be written as a function

$$U\left(T_s, T_f, T_w\right). \tag{5}$$

Therefore, the consumer's time allocation problem when she decides to visit n shops is an optimization problem in which she determines the time distribution (T_s, T_f, T_w) that maximizes her welfare (5) subject to the constraints (1)–(3).

In this paper two different consumer profiles are explored: *maximizer* and *satisficer*. Under a maximizing behavior, the consumer inspects all available market options – visits all the available sites –, which was denoted by N. Roughly speaking, a maximizer represents a consumer whose primary concern is to find – at any cost – the best option in the market. In contrast, under a satisficing behavior, the consumer reacts to the market price distribution by selecting optimally – in terms of welfare – how many sites to visit, say n^*, being $n^* \in \{1, \ldots, N\}$. Consequently, a maximizer solves a time distribution problem as presented above taking $n = N$, whereas a satisficer solves, additionally to a time allocation problem, the meta-problem of choosing the optimal number of shops to visit.

At first sight, the behavior of a maximizer might seem less rational than that of a satisficer, but classical economic theory offers a less clear-cut comparison. It is possible to interpret the maximizer behavior as a lexicographic preference ordering. It may be argued that the consumer's welfare has two components: price and utility, the former is perceived as a *bad* (lower is better) and the latter is a good which is formed from a specific time allocation. The maximizer sets lexicographic preference among those two components, once the first target – lowest price – is achieved, the second target – highest utility – is pursued. These kinds of preferences have been largely studied in economic theory and they meet some usual criteria of rationality, such as completeness or transitivity (see e.g. [7]).

3. Numerical analysis: method and input data

The framework above permits the analysis of different scenarios on regard to the consumer's behavior, the distribution of market prices and alternative specifications of functions G and τ. The analysis is organized by setting a benchmark case and then studying variations with respect to the benchmark. As it will be clear from the analysis, the choice of the benchmark is made to isolate the different trade-offs the consumer faces.

Under the benchmark case the consumer is a maximizer, prices are drawn from a Normal distribution and the inspection time per shop is given by

$$c(\mu, \sigma) = c_1 \left(1 + \frac{\sigma - \sigma_{min}}{\sigma_{max} - \sigma_{min}} + \frac{\mu - \mu_{min}}{\mu_{max} - \mu_{min}}\right), \tag{6}$$

where $c_1 > 0$. The different elements in (6) are introduced next. Combinations of pairs (μ, σ) are considered conforming an equispaced grid in a rectangle $\Theta := [\mu_{min}, \mu_{max}] \times [\sigma_{min}, \sigma_{max}]$. Clearly, the minimum value for c is $c(\mu_{min}, \sigma_{min}) = c_1$, whereas its maximum value is $c(\mu_{max}, \sigma_{max}) = 3c_1$. Basically, the range of c, which is $[c_1, 3c_1]$, is independent of its domain, Θ, which is a desirable feature since the domain and the range of c differ in its nature from one another.

Additionally, the utility function representing consumer's preferences is assumed to be a Cobb–Douglas function in logarithmic form, which is commonly used in economics. Specifically,

$$U\left(T_s, T_f, T_w\right) = a_1 \ln T_s + a_2 \ln T_f + a_3 \ln T_w,$$

where the a_i's are positive parameters. Notice that different signs for the parameters a_i's generate different consumer profiles, as pointed out in [6]. The case $a_i > 0$ corresponds with a balanced consumer profile, that is, it corresponds with a consumer who enjoys all possible uses of time—possibly in different ratios so that increases of different time uses have a different impact on his welfare. The set of values for the a_i's will be fixed throughout this paper. They are given in Table 1.

Table 1
Parameter values for the benchmark case.

Parameter(s)	Value(s)	Used in
T	200	Eq. (1)
(V, w)	(0, 6.5)	Eq. (2)
(a_1, a_2, a_3)	(0.25, 0.5, 0.25)	Eq. (5)
c_1	2	Eq. (6)
$[\mu_{min}, \mu_{max}]$	[600, 800]	Price sampling
$[\sigma_{min}, \sigma_{max}]$	[50, 150]	
$\mathcal{F}$	Normal	
N	20	

Finally, for each pair $(\mu, \sigma) \in \Theta$, G is defined as the expected value of the smallest order statistic in finite samples. To be precise, for an arbitrary $n \in \{1, \ldots, N\}$ let $S(n)$ denote a random sample of size n from the distribution $\mathcal{F}$, and let Y_n denote its minimum value, that is, $Y_n := \min\{S(n)\}$. Then

$$G(n) := \mathbb{E}[Y_n]. \tag{7}$$

Under the benchmark case, in which the consumer is a maximizer, only the evaluations of G and τ at $n = N$ are considered. Table 1 summarizes the parameter values for the benchmark case for all the parameters introduced above.

For each pair of values of $(\mu, \sigma) \in \Theta$, the consumer's problem is solved numerically. This is done in two steps. First, the expectation in (7) is estimated—goodness of fit is tested using the Kolmogorov–Smirnov test. Consider an arbitrary integer n. From K samples of size n of the distribution $\mathcal{F}$, K realizations of the random variable Y_n are obtained. Denote those realizations by $\{y_n^1, \ldots, y_n^K\}$. Then $G(n)$ is estimated by

$$G(n) \simeq \frac{1}{K} \sum_{k=1}^{K} y_n^k.$$

Second, as for the maximizer problem concerns (under the benchmark case), once $G(N, \mu, \sigma)$ and $\tau(N, \mu, \sigma)$ are computed for N given by its benchmark value (see Table 1), the corresponding time allocation problem described above is solved numerically. All time allocations problems are solved using a quasi-Newton method, namely the Broyden–Fletcher–Goldfarb–Shanno (*BFGS*) algorithm [8].

4. Results

4.1. The benchmark case: maximizer's response, welfare and σ-overload

Figs. 1 and 2 summarize the maximizer's response as μ and σ change in the case that prices are Normally distributed and shopping unit time is non-constant (the benchmark case). Specifically, Fig. 1 plots contour curves of U^* as a function of μ and σ, whereas Fig. 2 shows U^* vs. σ and U^* vs. μ, in panels (a) and (b), respectively. Both figures show that the consumers' welfare, as measured by U^*, decreases with μ, whereas it first increases and then decreases with respect to σ forming the inverted U-shape that shows panel (a) of Fig. 2. In other words, there is an optimal level of price dispersion in the market beyond which additional market dispersion makes the consumers worse off in terms of welfare. This is a significant negative effect on consumer's welfare. The consumer's discomfort is due to an overload in the spread of the set of prices. Notice that the size N of the set of prices does not increase but remains constant. This is a new phenomenon independent of N which may be called spread overload or σ-overload.

Table B.4 in Appendix B provides a quantitative assessment of the findings described above, particularly of the σ-overload effect. Basically a number of regression models have been run in which U^* is the response variable and μ and σ are the regressors or control variables. Table B.4 shows the estimates of a regression in each column. The columns differ from one another in the specification of non-linear effects, with empty cells whenever the correspondent term is not included in the regression. The main message in the table is that the coefficient of σ^2 (squared standard deviation) is statistically different from zero and negative at any usual confidence level in all of the columns. To summarize, the σ-overload effect, which is captured in the regressions as a function U^* of σ which is quadratic concave, is statistically robust to several model specifications.

Further results are presented in Appendix A to show that the previous findings are qualitatively robust to alternative distributional assumptions of the market prices. In order to isolate purely distributional effects, we consider a family of uniform distributions such that the range of first and second order moments coincide with those used for the benchmark case, that is, for each pair $(\mu, \sigma) \in \Theta$, prices are taken uniformly distributed in $[\mu - \sqrt{3}\sigma, \mu + \sqrt{3}\sigma]$. The corresponding results do replicate essentially those obtained under the benchmark case (see Figs. A.6 and A.7 in Appendix A and table Table B.5 in Appendix B).

A variation with respect to the benchmark case in which the unit shopping cost is independent of μ and σ is also included in Appendix A. In terms of Eq. (4), this study considers $\tau(n) = c_1 n$, where c_1 is given by its value in the benchmark case (see

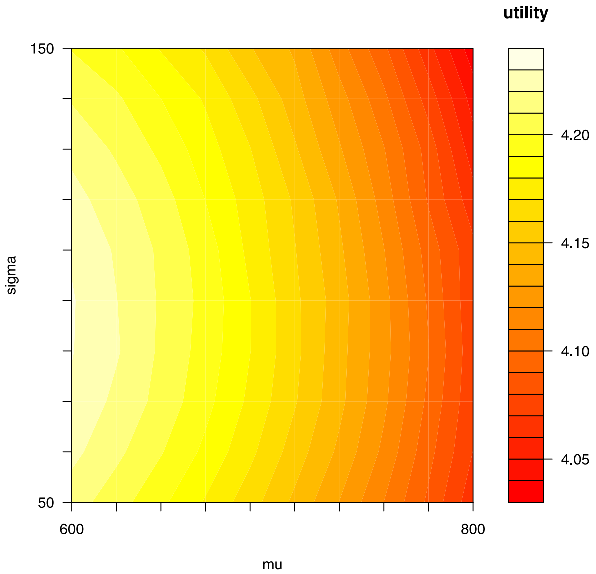
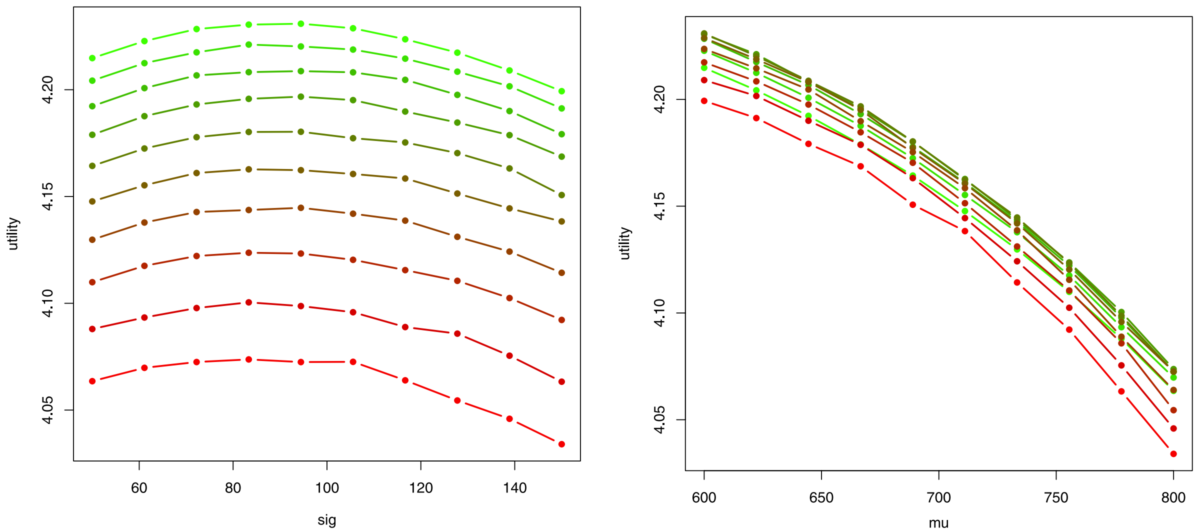


Fig. 1. Contour of U^* vs. μ and σ for the benchmark case.



(a) Utility vs. σ.

(b) Utility vs. μ.

Fig. 2. Utility vs. distributional parameters for the benchmark case. Each line in panel (a) corresponds to a fixed value of μ, with μ increasing as the color shifts from green to red, and analogously for the lines and colors in panel (b) with respect to σ. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1). The basic message, as compared to the benchmark case, is that the inverted-U relationship between U^* and σ is replaced by a monotonically increasing dependence (see Figs. A.8 and A.9 in Appendix A). Notice that the coefficient of σ^2 is not statistically different from zero, as it is shown in Table B.6.

4.2. The satisficer response: welfare, shopping strategy and σ-adaptation

In this section a behavioral departure from the benchmark case is analyzed. According to the definition in [1], the consumer is a satisficer if she does not explore all available options but only an sample of optimal size. Specifically, let Ω denote the subset of $\{1, \ldots, N\}$ such that the corresponding time allocation problem defined in Section 2 has a non-empty feasible set of time allocations. Given $n \in \Omega$, let $(T_s^*(n), T_f^*(n), T_w^*(n))$ denote the solution of the time allocation problem, and let $U^*(n) := U(T_s^*(n), T_f^*(n), T_w^*(n))$. The satisficer choice of n is given

$$n^* := \arg\max_{n \in \Omega}\{U^*(n)\}.$$

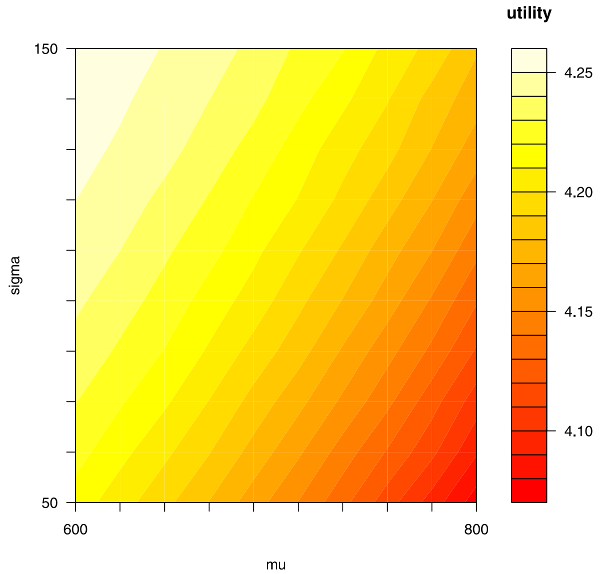
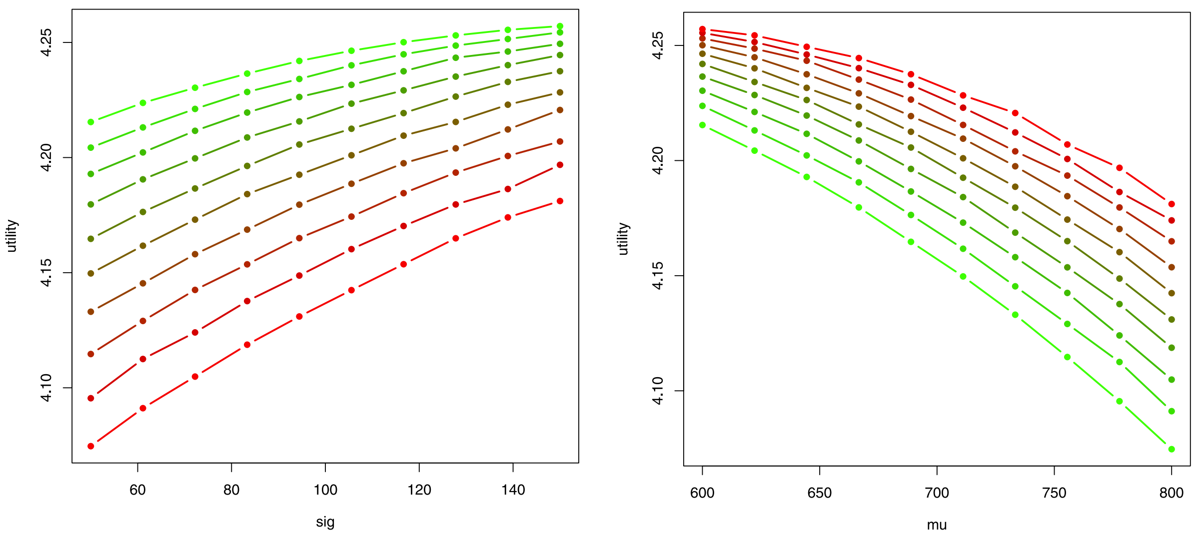


Fig. 3. Contour of welfare U^{**} vs. μ and σ for satisficing behavior.



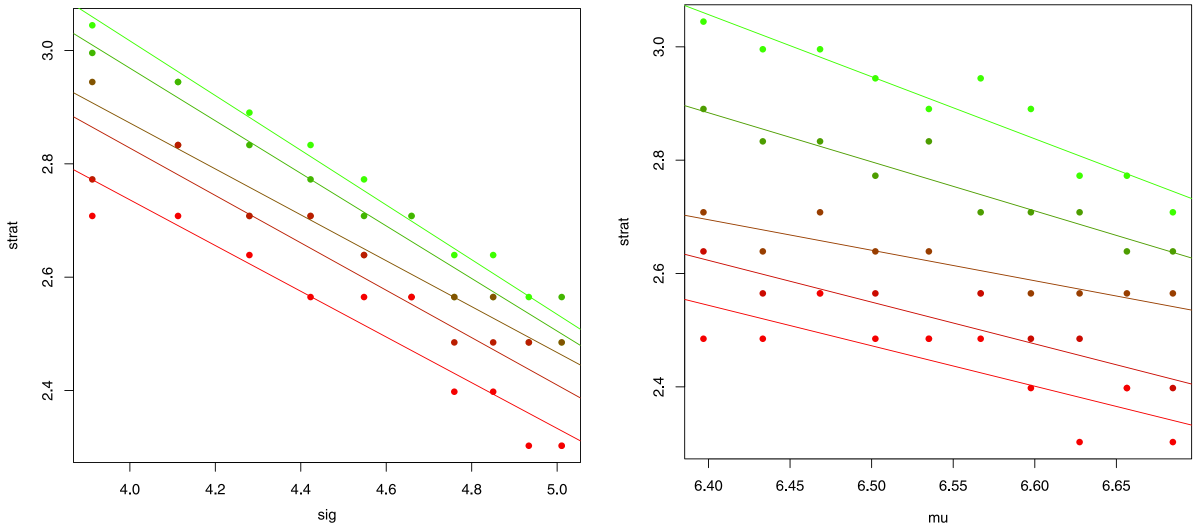
(a) Utility vs. σ.

(b) Utility vs. μ.

Fig. 4. Utility vs. distributional parameters for satisficer behavior. Each line in the panel (a) corresponds to a fixed value of μ, with μ increasing as the color shifts from green to red, and analogously for the lines and colors in panel (b) with respect σ. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Of course, the best strategy n^* and in turn the satisficer's welfare $U^{**} = U(n^*)$ depends on (μ, σ), once that $\mathcal{F}$ has been selected. The response of the satisficer (shopping strategy and welfare) to changes in (μ, σ) is analyzed below in the case that $N = 50$, thus n^* belongs to the set $\{1, \dots, 50\}$. Considering different values of N gives similar results.

Figs. 3 and 4 show the welfare analysis for the satisficer when μ and σ change. Fig. 3 plots contour curves of U^{**} as a function of μ and σ, while Fig. 4 displays plots of U^{**} vs. σ and of U^{**} vs. μ in panels (a) and (b), respectively. Both figures indicate that U^{**} increases with σ and decreases with μ, so that while the satisficer's welfare is directly related to price dispersion, it is inversely related to the average price. A standard statistical regression of U^{**} vs. μ and σ gives further support to these claims, as it can be seen in Table B.7 in Appendix B. The response of a satisficer's welfare to an increase in the price mean is thus similar to that of the maximizer: both consumers lose welfare as the price mean increases. However, in contrast to the case of a maximizer, the satisficer's welfare does not decrease when the total number or prices is widely spread, that is, a satisficer is not affected by σ-overload. On the contrary, this type of consumer increases her welfare as price dispersion increases. This is achieved by re-adapting suitably her shopping strategy when dispersion starts to be annoying. A satisficing behavior is thus capable to prevent the discomfort that is caused by a dispersed set of market prices.



(a) n^* vs. σ.

(b) n^* vs. μ.

Fig. 5. Shopping strategy n^* vs. distributional parameters for a satisficer's behavior. Each color in panel (a) corresponds to a fixed value of μ, with μ increasing as the color shifts from green to red. For each color, pairs (σ, n^*) are plotted together with the corresponding regression line (using the points of same color as data and taking n^* as dependent variable). From panel (a) to (b) σ and μ are interchanged. All magnitudes are in logs. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Shopping strategy vs. σ for different values of μ.

	Dependent variable: Shopping strategy				
	$\mu = 6.4$ (1)	$\mu = 6.47$ (2)	$\mu = 6.57$ (3)	$\mu = 6.63$ (4)	$\mu = 6.68$ (5)
σ	-0.483^{***} (0.022)	-0.464^{***} (0.036)	-0.405^{***} (0.028)	-0.418^{***} (0.056)	-0.403^{***} (0.047)
Constant	4.948^{***} (0.101)	4.824^{***} (0.166)	4.492^{***} (0.130)	4.500^{***} (0.255)	4.350^{***} (0.214)
Observations	10	10	10	10	10
R^2	0.983	0.953	0.962	0.875	0.902
Adjusted R^2	0.981	0.947	0.957	0.859	0.890
Residual std. error (df = 8)	0.024	0.040	0.031	0.061	0.051
F statistic (df = 1; 8)	475.563^{***}	162.586^{***}	202.898^{***}	55.845^{***}	73.909^{***}

Note:
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The absence of σ-overload in the satisficing behavior may be explained by an adaptive shopping strategy, that is, with the actual number of shops n^* that a satisficer decides to visit. The adaptation of the satisficer's shopping strategy n^* to changes in σ and μ is represented in Fig. 5. In a nutshell, the panels show that the satisficer visits a lower number of shops as either σ or μ increase—see panels (a) and (b) of Fig. 5, respectively. The lines in each panel of the figure are regression lines using the points of the corresponding color.

The estimated coefficients of those regressions can be seen in Tables 2 and 3, for panels (a) and (b) of Fig. 5, respectively. Consider first Table 2. To run different regressions of n^* on σ as μ changes imposes no restrictions on how the effect of σ on n^* is influenced by μ. The table shows a regression in each column, with the corresponding value of μ in the header of the column. Since all regressions are in logs, the estimated coefficient is the elasticity of n^* vs. σ. In all regressions the estimates are statistically different from zero and negative at any usual confidence level. Roughly, as the price dispersion (σ) increases by 1%, the number of visited shops (n^*) decreases by a percentage that ranks from 0.4% to nearly 0.5%, depending on the average market price (μ). Table 3 delivers a picture which is qualitatively similar – though with some more elastic responses – of n^* with respect to μ.

Therefore, a satisficer will not suffer from the σ-overload effect since visiting less sites in the market as the price dispersion increases leads to an improvement in welfare by considerably reducing shopping cost. Typically, a satisficer pays a price higher than the best deal in the market; what would reduce her welfare. However that welfare loss is counterbalanced by the welfare gains of reducing the shopping time when price dispersion rises.

Table 3
Shopping strategy vs. μ for different values of σ.

	Dependent variable: Shopping strategy				
	$\sigma = 3.91$ (1)	$\sigma = 4.28$ (2)	$\sigma = 4.66$ (3)	$\sigma = 4.85$ (4)	$\sigma = 5.01$ (5)
μ	-1.096^{***}	-0.866^{***}	-0.538^{***}	-0.737^{***}	-0.714^{***}
	(0.130)	(0.105)	(0.103)	(0.121)	(0.189)
Constant	10.072^{***}	8.423^{***}	6.141^{***}	7.339^{***}	7.111^{***}
	(0.854)	(0.689)	(0.676)	(0.792)	(1.241)
Observations	10	10	10	10	10
R^2	0.898	0.894	0.773	0.823	0.639
Adjusted R^2	0.886	0.881	0.744	0.801	0.594
Residual std. error (df = 8)	0.038	0.031	0.030	0.035	0.055
F statistic (df = 1; 8)	70.624^{***}	67.668^{***}	27.166^{***}	37.141^{***}	14.184^{***}

Note:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A different satisficer's response arises in the particular case that marginal shopping cost is constant and therefore independent of changes in both price mean and dispersion. This case was considered in [1], where it was first noticed the qualitative response of the shopping strategy to changes in mean and dispersion. The results shown in Figs. A.10–A.12 in Appendix A and in Tables B.8 and B.9 in Appendix B confirm the claims in [1], and provide an interesting quantitative assessment of the satisficer's response. Notice that in this case – shopping cost independent of μ and σ – the σ-adaptation consists of visiting more sites as price dispersion increases. So, a 1% increase in the standard deviation of the price distribution implies an increase of 0.236% in the number of visited sites (see Table B.9). Since more price dispersion is costless in this particular case, a satisficer here will visit more sites, get better deals and also enjoy more welfare. This shopping behavior differs from that of the satisficer considered first in this section. That type of consumer faces shopping costs that are directly related with the mean price and price dispersion, which seems a more realistic assumption in typical scenarios.

5. Conclusions

A consumer typically visits a number of shops to find a best deal in the market, however this is costly in terms of shopping time. In this paper shopping behavior is derived as a by-product of a rational decision-making on the allocation of time among alternative uses. Since different shops usually set different prices, the way in which market prices are distributed may have a significant impact on the consumer's shopping time and thus on her welfare. Also, different psychological attitudes towards shopping may influence consumer's welfare. So, a maximizer looks for the best no matter the cost a priori whereas a satisficer opts for something just satisfactory, namely the best option within a sample of the total number of available options.

If market prices are somehow redistributed in a way that the average price rises, consumer's welfare will decrease in general. This fact is confirmed in this paper both for maximizers and satisficers under a general shopping cost structure. The effect of price dispersion on consumer's welfare may appear not so clear at first sight. It seems apparent that some dispersion is better than none. In fact, both maximizers and satisficers' welfare improve when the increase in dispersion occurs at low levels of dispersion. However, at higher levels of price dispersion it is shown here that a maximizer's welfare decreases with further dispersion. This response of welfare as an inverted-*U* with respect to the standard deviation of the price distribution is a new adverse effect for the consumer that it is called here σ-overload. In contrast to the well-known choice overload effect, due to an increase in the number of options in a choice set, σ-overload may appear for a fixed number of options that are widely spread when arranged or ranked according to some (quantitative) feature—price in this paper.

Also, it is shown here that satisficers whose shopping time directly correlates with price mean and dispersion avoid σ-overload by adapting their shopping behavior to more dispersion; in particular, they visit less shops as price dispersion increases – and also as the average market price is higher – what keeps their welfare increasing. This behavior is called σ-adaptation in this paper. A quantitative assessment of the σ-adaptation effect is also provided in the paper: numerical estimates are obtained for the increase in the number of shops visited as a response to a marginal increase in the average price or in the dispersion. These estimates provide valuable information for the seller side of the market, e.g. when pricing its product, a firm can anticipate the consumer's response to different price distributions.

Acknowledgments

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Appendix A. Departures from the benchmark

A.1. Prices uniformly distributed

This section considers the scenario in which the distribution generating the market prices is uniform, all else being equal to the benchmark case. As it is apparent from the figures, the results do not differ qualitatively from those obtained in the main text for the Normal distribution.

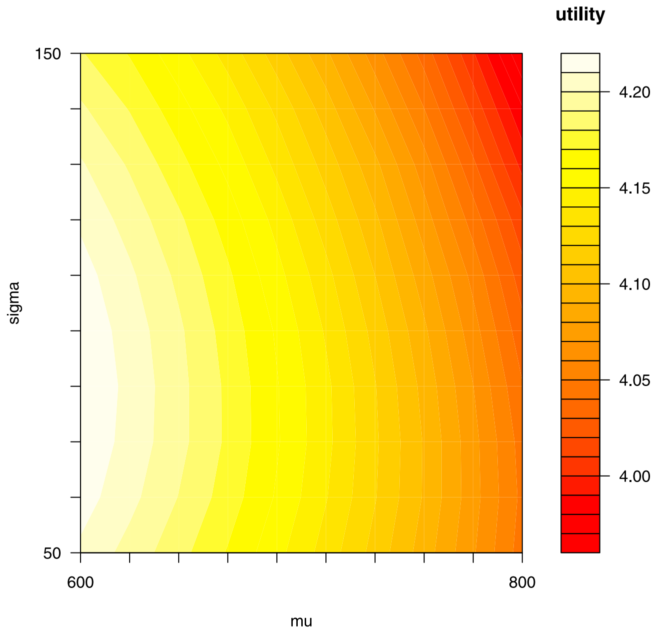
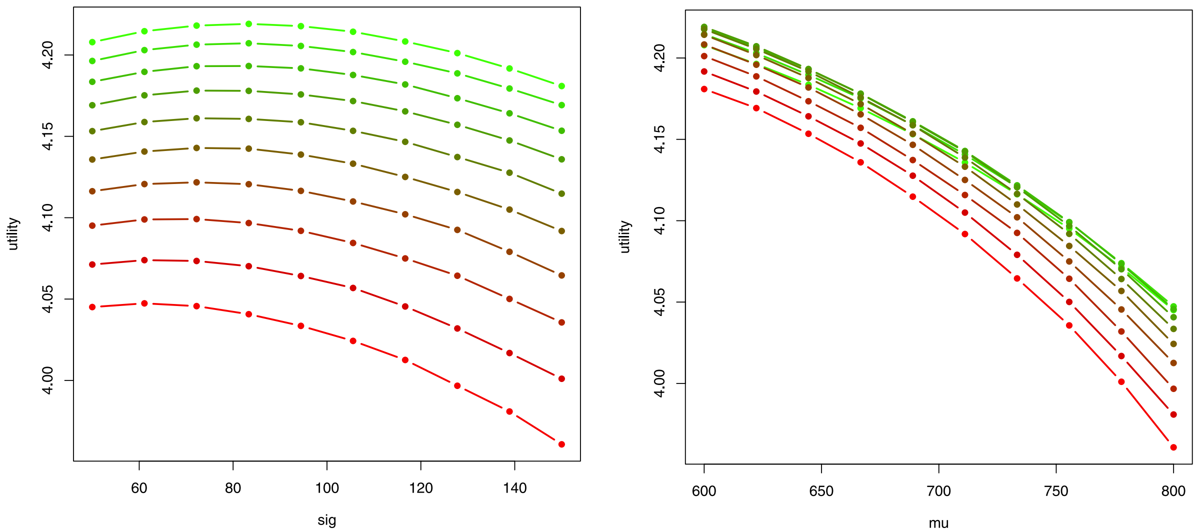


Fig. A.6. Contour of U^* vs. μ and σ, benchmark except for market prices that are uniformly distributed.



(a) Utility vs. σ.

(b) Utility vs. μ.

Fig. A.7. Utility vs. distributional parameters, benchmark except for market prices that are uniformly distributed.

A.2. Constant shopping unit cost

This section analyzes the case in which the shopping cost per shop/site is constant, all else being equal to the benchmark case. In this case, no additional shopping cost is imposed for the consumer as price mean and dispersion change marginally. This fact entails new implications with respect to the results obtained to the benchmark case. Figs. A.8 and A.9 show that here welfare is directly related to an increase in price dispersion and inversely related to an increase in the average price.

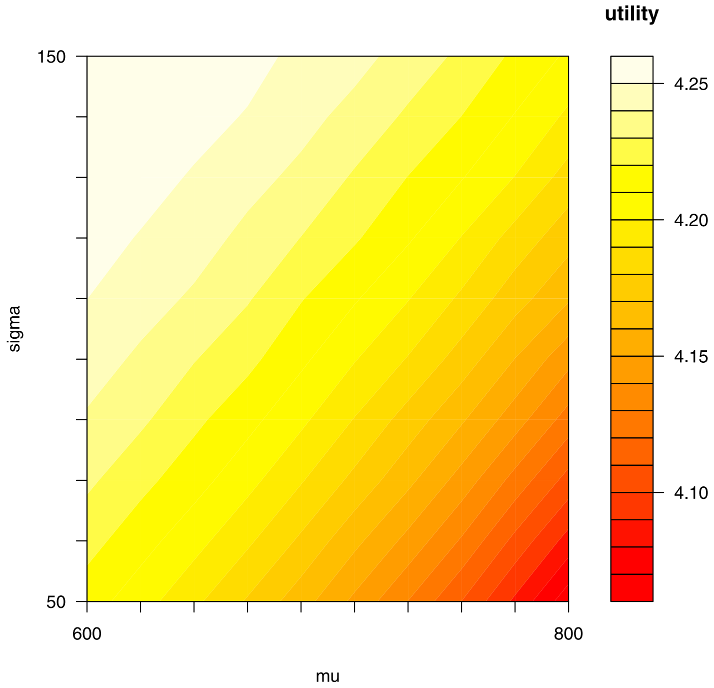


Fig. A.8. Contour of U^* vs. μ and σ, benchmark except for constant shopping unit cost.

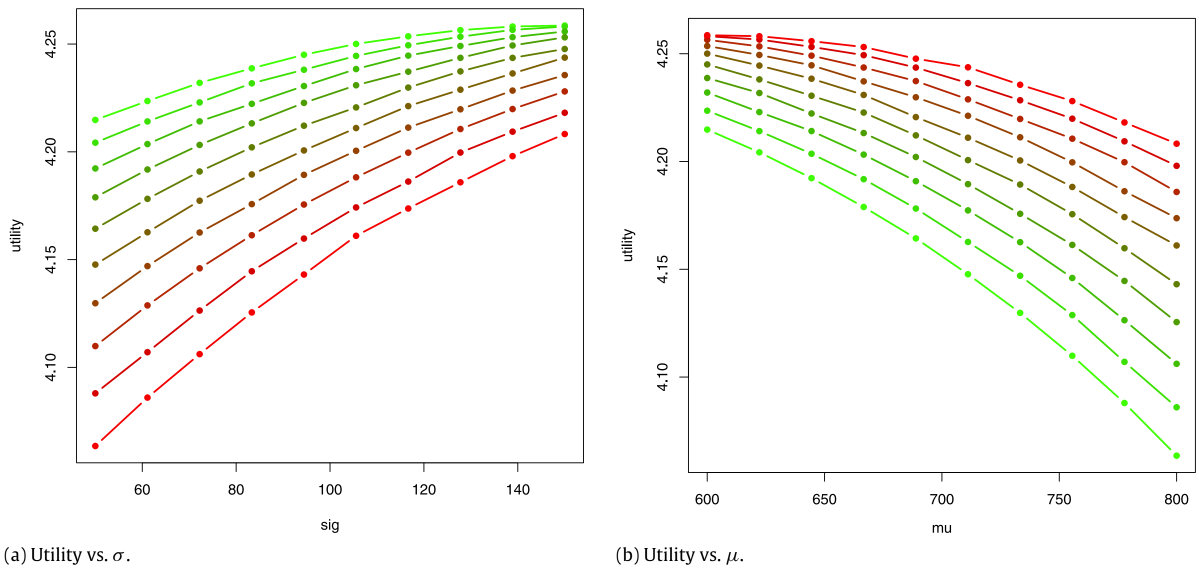


Fig. A.9. Utility vs. distributional parameters, benchmark except for constant shopping unit cost.

A.3. Satisficing behavior and constant shopping unit cost

This section shows the results for the case in which the shopping cost per site is constant, all else being equal to the benchmark case. Here no further shopping cost is faced by the satisficer as price mean and dispersion increases. This fact produces different results with respect to the benchmark case. Figs. A.10 and A.11 show that welfare in this case is directly related to an increase in price dispersion and inversely related to an increase in the average market price.

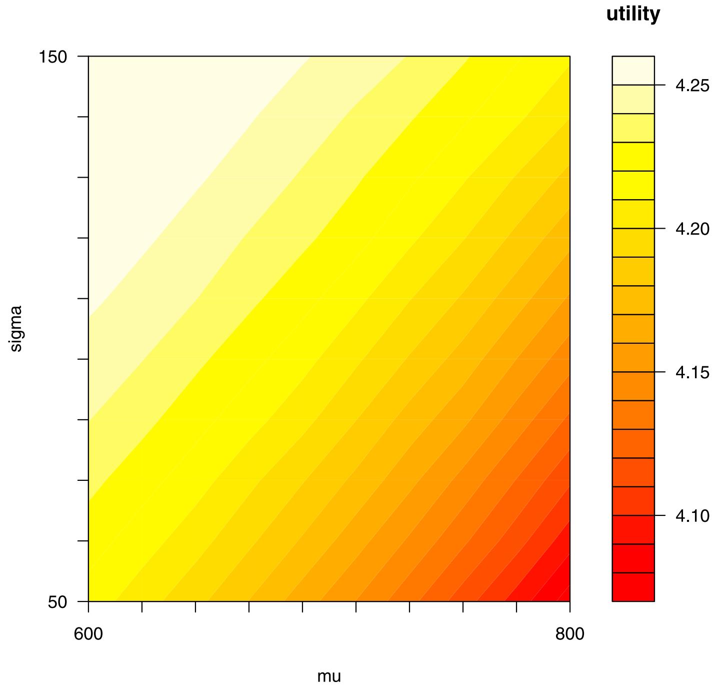


Fig. A.10. Contour of U^* vs. μ and σ, benchmark except for constant shopping unit cost and satisficing behavior.

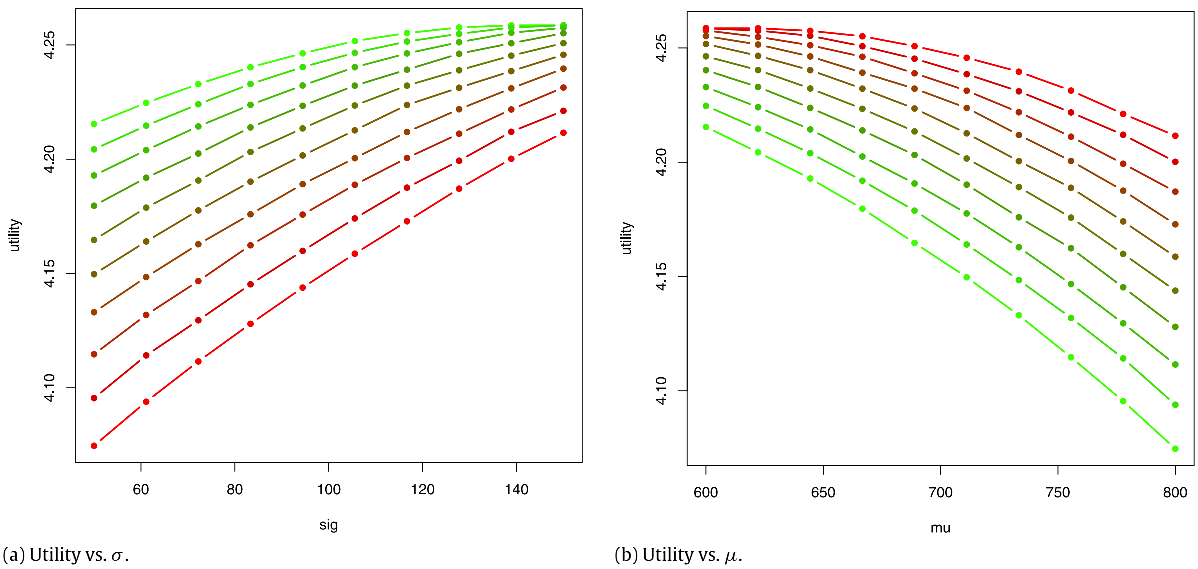
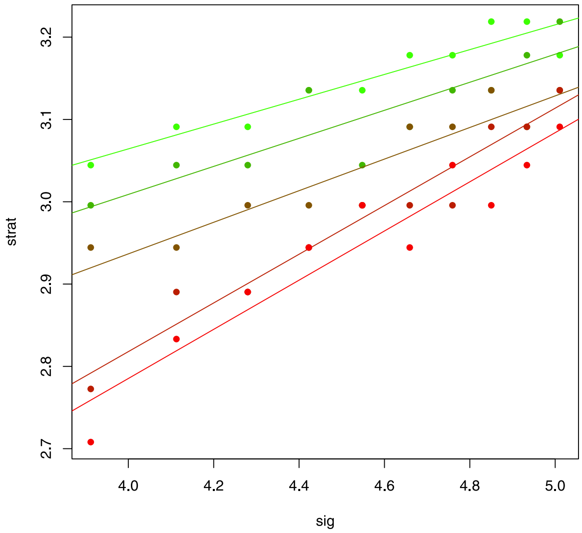
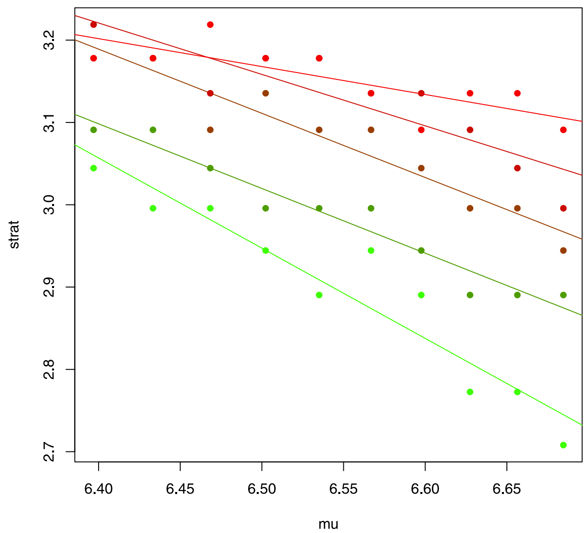


Fig. A.11. Utility vs. distributional parameters, benchmark except for constant shopping unit cost and satisficing behavior.



(a) n^* vs. σ.



(b) n^* vs. μ.

Fig. A.12. Shopping strategy n^* vs. distributional parameters for a satisficer with constant shopping unit cost. Each color in panel (a) corresponds to a fixed value of μ, with μ increasing as the color shifts from green to red. For each color pairs (σ, n^*) are plotted together with the regression line (using points of same color as data and taking n^* as dependent variable). From panel (a) to (b) σ and μ are interchanged. All magnitudes are in logs. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Appendix B. Regressions

The section contains all the regression analysis. All regressions are in logs. All tables include four different regressions, depending on which regressors are used. Typically, the first regression in all tables shows direct/linear impact of price dispersion and price mean (in logs) on utility (also in logs), while the other three regressions in each table capture different nonlinear effects of these same variables.

The main message from Table B.4 is the concavity of the quadratic term of the price dispersion, that is, the negative coefficient of σ^2 which is significant for all the regressions. Table B.5 confirms this very fact for the case in which prices are uniformly distributed.

Table B.6 suggests that a maximizer with constant shopping unit cost (independent of price mean and dispersion) implies that a higher dispersion or also a lower mean of prices improve the consumer's welfare; this is supported by the negative coefficient for μ and the positive coefficient for σ in the first regression – both significant at several levels –. Similar results are obtained for a satisficer, as suggested in Tables B.7 and B.8.

A satisficer with constant shopping unit cost (independent of price mean and dispersion) will check more options the higher the dispersion or the lower the mean; this is supported by the negative coefficient for μ and the positive coefficient for σ in the first regression of Table B.9—both significant.

Table B.4
Regressions for the benchmark case.

	Dependent variable: Utility			
	(1)	(2)	(3)	(4)
μ	−0.131***	−0.086**	4.178***	4.134***
	(0.004)	(0.037)	(0.121)	(0.132)
σ	−0.003***	0.228***	0.228***	0.163***
	(0.001)	(0.057)	(0.015)	(0.006)
$\mu \times \sigma$		−0.010	−0.010***	
		(0.008)	(0.002)	
μ^2			−0.326***	−0.326***
			(0.009)	(0.010)
σ^2		−0.019***	−0.019***	−0.019***
		(0.002)	(0.001)	(0.001)
Constant	2.295***	1.632***	−12.315***	−12.022***
	(0.024)	(0.247)	(0.400)	(0.434)

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Table B.4 (*continued*)

	Dependent variable: Utility			
	(1)	(2)	(3)	(4)
Observations	100	100	100	100
R^2	0.933	0.960	0.997	0.997
Adjusted R^2	0.931	0.958	0.997	0.996
Residual std. error	0.003 (df = 97)	0.003 (df = 95)	0.001 (df = 94)	0.001 (df = 95)
F statistic	674.123*** (df = 2; 97)	563.899*** (df = 4; 95)	6637.194*** (df = 5; 94)	6867.324*** (df = 4; 95)

Note:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.5
Regressions for uniformly distributed prices.

	Dependent variable: Utility			
	(1)	(2)	(3)	(4)
μ	−0.157***	0.041	4.948***	4.751***
	(0.005)	(0.043)	(0.160)	(0.295)
σ	−0.010***	0.480***	0.480***	0.196***
	(0.001)	(0.067)	(0.020)	(0.014)
$\mu \times \sigma$		−0.043***	−0.043***	
		(0.009)	(0.003)	
μ^2			−0.375***	−0.375***
			(0.012)	(0.023)
σ^2		−0.023***	−0.023***	−0.023***
		(0.003)	(0.001)	(0.002)
Constant	2.489***	0.739**	−15.310***	−14.017***
	(0.030)	(0.288)	(0.529)	(0.966)
Observations	100	100	100	100
R^2	0.929	0.964	0.997	0.989
Adjusted R^2	0.928	0.962	0.997	0.988
Residual std. error	0.004 (df = 97)	0.003 (df = 95)	0.001 (df = 94)	0.002 (df = 95)
F statistic	637.547*** (df = 2; 97)	630.467*** (df = 4; 95)	5702.554*** (df = 5; 94)	2070.529*** (df = 4; 95)

Note:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6
Regressions when unit search cost is constant.

	Dependent variable: Utility			
	(1)	(2)	(3)	(4)
μ	−0.081***	−0.431***	2.168***	2.518***
	(0.003)	(0.023)	(0.079)	(0.448)
σ	0.020***	−0.489***	−0.489***	0.015
	(0.001)	(0.035)	(0.010)	(0.021)
$\mu \times \sigma$		0.077***	0.077***	
		(0.005)	(0.001)	
μ^2			−0.199***	−0.199***
			(0.006)	(0.034)
σ^2		0.001	0.001	0.001
		(0.001)	(0.0004)	(0.002)
Constant	1.870***	4.175***	−4.323***	−6.617***
	(0.021)	(0.152)	(0.262)	(1.466)
Observations	100	100	100	100
R^2	0.926	0.979	0.998	0.945
Adjusted R^2	0.924	0.978	0.998	0.943
Residual std. error	0.003 (df = 97)	0.002 (df = 95)	0.0004 (df = 94)	0.003 (df = 95)
F statistic	606.095*** (df = 2; 97)	1104.145*** (df = 4; 95)	11,156.800*** (df = 5; 94)	410.569*** (df = 4; 95)

Note:
* $p < 0.1$,** $p < 0.05$, *** $p < 0.01$.

Table B.7
Regression under satisficer behavior.

	Dependent variable: Utility			
	(1)	(2)	(3)	(4)
μ	−0.088***	−0.319***	2.217***	2.447***
	(0.002)	(0.022)	(0.051)	(0.295)
σ	0.017***	−0.329***	−0.329***	0.002
	(0.001)	(0.033)	(0.006)	(0.014)
$\mu \times \sigma$		0.051***	0.051***	
		(0.005)	(0.001)	
μ^2			−0.194***	−0.194***
			(0.004)	(0.023)
σ^2		0.002	0.002***	0.002
		(0.001)	(0.0003)	(0.002)
Constant	1.938***	3.478***	−4.814***	−6.324***
	(0.016)	(0.145)	(0.169)	(0.964)
Observations	100	100	100	100
R^2	0.954	0.979	0.999	0.974
Adjusted R^2	0.953	0.978	0.999	0.973
Residual std. error	0.002 (df = 97)	0.002 (df = 95)	0.0003 (df = 94)	0.002 (df = 95)
F statistic	1007.150*** (df = 2; 97)	1119.964*** (df = 4; 95)	24,773.100*** (df = 5; 94)	902.344*** (df = 4; 95)

Note:
* $p < 0.1$,** $p < 0.05$, *** $p < 0.01$.

Table B.8
Regression under satisficer behavior and constant inspection unit cost.

	Dependent variable: Utility			
	(1)	(2)	(3)	(4)
μ	−0.079***	−0.401***	2.079***	2.402***
	(0.003)	(0.022)	(0.089)	(0.415)
σ	0.020***	−0.461***	−0.461***	0.003
	(0.001)	(0.034)	(0.011)	(0.019)
$\mu \times \sigma$		0.071***	0.071***	
		(0.005)	(0.002)	
μ^2			−0.190***	−0.190***
			(0.007)	(0.032)
σ^2		0.002	0.002***	0.002
		(0.001)	(0.0005)	(0.002)
Constant	1.862***	4.011***	−4.102***	−6.212***
	(0.020)	(0.147)	(0.296)	(1.359)
Observations	100	100	100	100
R^2	0.933	0.979	0.998	0.951
Adjusted R^2	0.931	0.979	0.998	0.949
Residual std. error	0.003 (df = 97)	0.002 (df = 95)	0.001 (df = 94)	0.002 (df = 95)
F statistic	671.494*** (df = 2; 97)	1134.630*** (df = 4; 95)	8449.501*** (df = 5; 94)	464.326*** (df = 4; 95)

Note:
* $p < 0.1$,** $p < 0.05$, *** $p < 0.01$.

Table B.9
Regression under satisficer behavior and constant inspection unit cost.

	Dependent variable: Shopping strategy			
	(1)	(2)	(3)	(4)
μ	−0.697***	−3.378***	4.654	7.335
	(0.038)	(0.423)	(5.151)	(6.121)
σ	0.236***	−3.626***	−3.626***	0.232
	(0.010)	(0.653)	(0.648)	(0.287)
$\mu \times \sigma$		0.589***	0.589***	
		(0.093)	(0.092)	

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Table B.9 (*continued*)

	Dependent variable: Shopping strategy			
	(1)	(2)	(3)	(4)
μ^2			−0.614	−0.614
			(0.392)	(0.468)
σ^2		0.0005	0.0005	0.0005
		(0.027)	(0.027)	(0.032)
Constant	6.536***	24.097***	−2.170	−19.721
	(0.252)	(2.820)	(17.020)	(20.029)
Observations	100	100	100	100
R^2	0.902	0.931	0.933	0.904
Adjusted R^2	0.900	0.928	0.929	0.900
Residual std. error	0.035 (df = 97)	0.029 (df = 95)	0.029 (df = 94)	0.035 (df = 95)
F statistic	446.681*** (df = 2; 97)	321.959*** (df = 4; 95)	261.983*** (df = 5; 94)	223.131*** (df = 4; 95)

Note:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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