Behavioral Interventions under Strategic Pricing

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Abstract

Behavioral interventions, such as awareness campaigns or nudges, change the demand of few consumers but trigger a retail price reaction felt by all. In a theoretical model, I determine when and to what extent this price effect matters depending on market conditions. I also characterize which demand change among the few consumers is optimal to maximize the consumption of a given good by all. Making consumers more willing to pay may decrease consumption overall, while making them more sensitive to prices prevents opportunistic price reactions. I illustrate the empirical relevance of these findings with a structural model of a food industry calibrated on consumer panel data.

1 Introduction

Our day-to-day grocery shopping, however minor it may seem, has major environmental consequences. Food systems are known to be responsible for roughly 30% of greenhouse gas emissions globally [Willett et al., 2019]. They are also major drivers of water use and pollution, deforestation and biodiversity loss. The transition to more sustainable production modes cannot happen without dramatic changes in daily consumption choices. For instance, the EU Farm to Fork strategy [European Commission, 2020] has set ambitious targets for the development of organic farming - an agricultural practice deemed beneficial for biodiversity - and calls for the reorientation of advertising towards more sustainable products, the implementation of front-of-pack labeling and the spread of digital-based environmental information tools to raise the demand for this industry.

Such behavioral interventions are increasingly used to promote sustainable consumption when typical price-based instruments such as taxes and subsidies are off the table. Yet, sales of organic food have stalled in France in 2021 after a decade of two-digit growth [Agence BIO, 2022], in spite of rising advertising budgets [LSA Conso, 2022] awareness campaigns and access to environmental information through barcode scanning apps. Organic food, just as many green products, struggles to become more than a niche market. Some suggest to increase the dose as a remedy: making the environmental qualities even more salient to further increase the correspoonding consumer willingness to pay. Is it really the change in purchasing behavior that behavioral interventions should aim at in order to maximize green consumption?

In this paper, I argue that pro-environmental behavioral interventions should rather make consumers more sensitive to prices than more willing to pay for green products. Being sensitive to prices means that one's consumption of a good varies sharply depending on whether its price is below or above a reference level. Examples of behavioral interventions making consumers more sensitive to prices are price advertising [Kaul and Wittink, 1995], making prices more visible at the point of sales, imposing the display of a reference price [Ater and Avishay-Rizi, 2022], providing price comparison tools or even launching a price-related boycott movement [Hendel et al., 2017].

Two key observations that point towards this approach are that 1) retailers price green products based on consumer demand and 2) consumers reacting to pro-environmental behavioral interventions tend to be few, purchasing green more often [Taillie et al., 2022, Lohmann et al., 2022] and less sensitive to prices [Yue et al., 2020] than others. Under perfect competition, prices would be determined by costs and left unaffected by behavioral interventions. In practice, increasing consumer willingness to pay for environmental qualities is likely to result in higher retail prices. One usually thinks of pro-environmental interventions as triggering a uniform increase in willingness to pay in a relatively homogeneous population, which - in spite of the increase in price due to strategic pricing - would still lead to a rise in green consumption overall. However, since consumers are actually quite heterogeneous in their willingness to pay for the green good before and even more so after usual interventions, the direction of the change in demand is ambiguous. Conversely, making consumer more sensitive to prices might foster competition, push prices down and make them more affordable to consumers that are less willing to pay. I call "price effect" this indirect change in green consumption due to the price response of the retailer following an intervention.

This paper uses both a theoretical model and simulations based on a structural model calibrated on consumer panel data to validate the previous rationale. I consider changes in purchasing behavior that could result from plausible behavioral interventions and I investigate which would be most beneficial to green consumption overall. I find that the price effect matters for the design and evaluation of pro-environmental behavioral interventions and that making consumers more sensitive to prices can reverse the opportunistic price response by the retailers, to the benefit of green consumption.

I first introduce a theoretical model of how behavioral interventions affect the price and consumption of a good under monopoly pricing. Behavioral interventions are changes in the demand function of a given fraction of the consumers. The problem of intervention design consists in choosing the purchasing behavior of these consumers so as to maximize the consumption of the good in the whole population once prices will have adjusted. I define the price effect as the change in consumption that is due to the price response, as opposed to the behavioral effect, the change in demand that would have been observed after the intervention if the price had remained constant.

I show that optimal interventions induce a non-negative price effect and make the fraction of consumers extremely sensitive to price changes in order to exert pressure on the supply-side. I derive an estimate of the magnitude of the price effect for interventions affecting only a small share of consumers. This assumption does not mean that the good is consumed by few, but that the intervention can only change the behaviour of few consumers. Under this assumption, I determine an upper bound on the price effect and I show that it is larger than the behavioral effect in optimal interventions. The results of the theoretical model are extended to the case of a multi-product monopolist and symmetrical Nash-Bertrand oligopolists.

I then study empirically whether the assumptions of the theoretical model are met in practice. I estimate a structural model of the demand and supply for eggs at major French retailers in 2012 - with organic eggs as the reference green product. The demand model is a multinomial logit model with random coefficients on price sensitivity and valuation of the organic attribute. It is estimated on home-scanned purchase data from a consumer panel representative of the French population. Even though organic eggs enjoy a large utility premium, their even larger prices limit their market share to 10%. Computing the Bayesian posterior means of the random coefficients, I obtain household-level estimates for price-sensitivity and willingness to pay for the organic attribute. I find that consumers willing to pay the most for organic attributes turn out to be also less price-sensitive than others. The supply model assumes Nash-Bertrand oligopolistic competition and constant marginal costs. The latter can be retrieved from the first-order condition at the initial equilibrium, knowing prices, demand and demand elasticities. I find that retailers indeed set higher margins on organic eggs than on unlabeled eggs.

Having calibrated my model, I can simulate behavioral interventions. The previous theoretical model considered very general demand functions and changes in demand but imposed restrictive assumptions on the supply-side. Using the structural model, I make realistic supply-side assumptions but I restrict the type of changes in demand that I consider. I introduce behavioral interventions in the structural model by changing the household-level willingness to pay and price sensitivity parameters for a small subset of the population in the demand model and computing the new market equilibrium. Raising the willingness-to-pay is the acknowledged objective of many interventions in the literature. Raising the price sensitivity is what optimal interventions should do according to my theoretical model. I compare interventions varying in their type (raising consumer willingness to pay or price sensitivity), targeting (which consumers change their purchasing behavior) and scale (how many consumers change their behavior).

I find that raising the willingness to pay for the organic label, be it among low price-sensitivity consumers or among consumers with a high willingness to pay for the organic label, has a limited effect on organic consumption overall because of the price effect. Conversely, making these consumers more price-sensitive can significantly increase total organic consumption, even when the population affected by the intervention purchases mostly organic eggs at current prices. The intuition behind this mechanism is that, in a niche market, prices are set based on the consumers that are willing to pay the most for the product.

Related literature

It is common in empirical IO studies of food markets to consider that retailers adapt their prices to policy interventions. This approach has not only been applied to price-based policies, but also to behavioral interventions such as mandatory front-of-pack nutritional labels [Allais et al., 2015a] and a hypothetical ban of advertising for junk food [Dubois et al., 2018]. The usual conclusion is that the price reaction of the firms strongly attenuates the intended effect of the policy.

The closest related work in this literature might be Villas-Boas et al. [2020], which measures experimentally how several nutritional labels change the demand curve and use this to simulate the retailers' strategic price response if the intervention was implemented at scale. The conclusions of my paper are much more general: since I abstract from how interventions are implemented to focus on how they affect the demand curve, I can explore a much wider range of interventions, both theoretically and in simulations.

My theoretical model is in essence very similar to Johnson and Myatt [2006]. This other article asks how the incentives of a firm vary when the demand curve it faces is modified. Using its terminology, raising consumer willingness to pay means shifting the demand curve rightwards, whereas making consumers more sensitive to prices means rotating it anticlockwise. Johnson and Myatt [2006] find that, in niche markets, firms prefer spreading consumer willingness to pay, while in mass market, they prefer to gather it around a specific value. The results of my theoretical model provide a reinterpretation of this insight: gathering consumer willingness to pay around a well-chosen price is an optimal way to transition from niche to mass market.

Finally, Hendel et al. [2017] provide a thorough empirical analysis of a large intervention having made consumers more sensitive to prices. This article studies a boycott on cottage cheese that took place in 2011 in Israel and documents the key role of the rise in price sensitivity in explaining the long-lasting price cuts that followed the boycott. The boycott rule implemented by the movement turns out to belong to a class of optimal behavioral interventions analyzed in my theoretical model. While Hendel et al. [2017] is an ex-post analysis, my article can be understood as providing theory- and simulation-based methods to predicting ex-ante the price effect of behavioral interventions.

2 Theory

This section provides a model of how behavioral interventions affect the price and demand for a good. I first introduce the model notations and formalize the idea of a "price effect", the change in consumption due to the firm price response to a behavioral intervention. I focus on the consumption of a good sold by a monopolist firm and introduce the behavioral intervention as a change in the demand function of some consumers. In this setting, I then study what type of purchasing behavior should be induced by behavioral interventions in order to maximize the consumption of the good (understood as a green good). I find that, in optimal interventions, affected consumers lower their demand at current price in order to obtain a price cut, which increases the consumption of the green good among non-affected consumers. Finally, I derive formulas for the magnitude of the price change following small-scaled interventions and conclude that the price effect plays a major role in all optimal behavioral interventions.

2.1 Notations and mechanisms

I analyze a setting where a monopolist sells at a price p an homogeneous good, acquired at a constant marginal cost c. The firm generates a profit $\Pi(p) = D(p)(p-c)$ where $D(p)$ is the aggregate demand for the good.

To keep the model simple, there is just one good, understood as being green, and I consider that the policy objective is to maximize the consumption of this good. I do not include explicitly brown good consumption. The effect of brown good consumption on pricing decisions can be safely ignored if the price of the brown good is fixed - for instance, due to strong competitive pressure. It can also be ignored from an environmental policy perspective as long as consuming the brown good is as detrimental to the environment as other plausible outside options external to the market.

The consumer population is split ex ante between the consumers that are affected (A) by the intervention and those that are not (N) - neutral consumers. The aggregate demand for the green good can thus be decomposed as $D(p) = D^A(p) + D^N(p)$, with one aggregate demand function per consumer group.

There are two periods, (1) before and (2) after the intervention. In period $i \in \{1,2\}$, the aggregate demand among affected consumers is $D_i^A(p)$ and the price p_i is set by the firm to maximize the profit function $\Pi_i(p) = D_i(p)(p-c) = (D_i^A(p) + D^N(p))(p-c)$. When several prices yield the same profit, I assume that the firm picks the lowest. I also assume that all the demand functions are asymptotically dominated by the inverse of the price, so that the corresponding profit functions tend to zero as the price goes to $+\infty$. Thus, equilibrium prices are always well-defined.

The purchasing behavior of affected consumers after the intervention, D_2^A, is the main policy choice analyzed in the paper. In this theory section, I obtain some results that are valid for any intervention-induced purchasing behaviors D_2^A, not just for the two specific cases of interventions

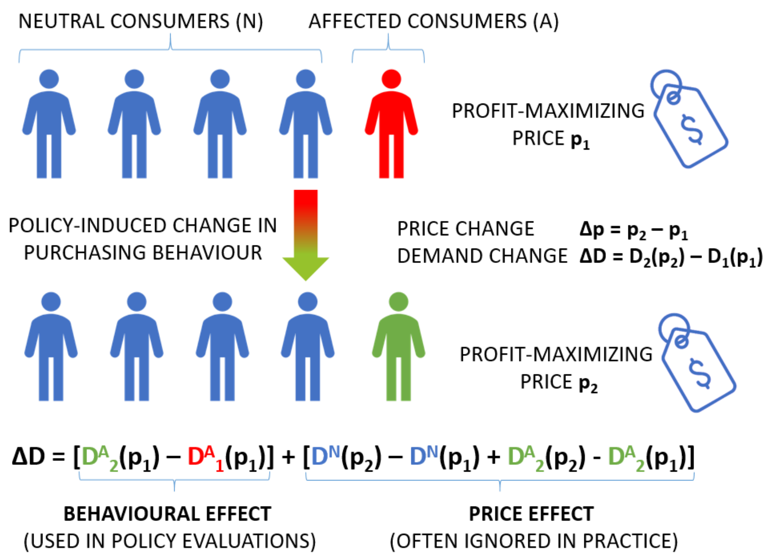


Figure 1: The effects of a behavioral policy in the model

raising consumer willingness to pay and interventions raising consumer price sensitivity. The purchasing behavior of affected consumers before the intervention, D_1^A, depends on the targeting of the intervention.

The policy objective is to maximize the final (green good) consumption $D_2(p_2)$ - or equivalently, the change in demand, denoted $\Delta D = D_2(p_2) - D_1(p_1)$. Another interesting outcome variable is the change in price, denoted $\Delta p = p_2 - p_1$.

The main argument of the paper can be understood from the following accounting identity :

$$\Delta D = \underbrace{\left[D_2^A(p_1) - D_1^A(p_1)\right]}_{\text{behavioral effect}} + \underbrace{\left[D_2^N(p_2) - D_1^N(p_1) + D_2^A(p_2) - D_2^A(p_1)\right]}_{\text{price effect}} \tag{1}$$

The first term $\left[D_2^A(p_1) - D_1^A(p_1)\right]$ captures the demand change taking place in the affected population before the price response of the firm, which I call the behavioral effect. It is the typical outcome variable used in the experimental evaluation of behavioral interventions.

The second term captures the consumption change due to the price response of the firm to the intervention, which I call the "price effect". The term $D_2^A(p_2) - D_2^A(p_1)$ is arguably of second order in many interventions because both the affected population size and the corresponding price change are small. However, there is no reason to think that the same goes for $D_2^N(p_2) - D_1^N(p_1)$.

The main argument of the paper is that $D_2^N(p_2) - D_1^N(p_1)$ should not be ignored when designing and evaluating behavioral interventions.

2.2 Optimal induced purchasing behavior

In this subsection, I ask what purchasing behavior should be triggered by behavioral interventions to achieve the policy objective of raising consumption. I call "optimal" any induced purchasing behavior D_2^A such that the equilibrium demand $D_2(p_2)$ is maximized. Of course, this question only makes sense if there is somehow a limit to green consumption in the affected population.

To formalize this idea, let us impose the constraint that $0 \leq D_i^A(p) \leq \varepsilon$ for $p \in \mathbb{R}$ and $i \in \{1,2\}$. One can interpret ε as the share of affected consumers, when each of them has a unit demand. This reflects both the fact that the behavioral effect is limited by the number of affected consumers and the extent to which their demand for the green good is already saturated.

Formally, the problem of finding an optimal intervention writes as follows:

$$\begin{aligned}
\text{Maximize } D_2(p_2) = D_2^A(p_2) + D^N(p_2) \text{ over the choice of } D_2^A \\
\text{such that } 0 \leq D_2^A(p) \leq \varepsilon \text{ for all } p > 0 \\
\text{and } p_2 = \underset{p>0}{\arg\max} \left[D_2^A(p) + D^N(p) \right] (p - c)
\end{aligned}$$

I will show that it is optimal that affected consumers stop purchasing the green good when its price is above a given threshold, and always purchase it otherwise. Let me call the corresponding demand function a cut-off purchasing behavior.

Definition 1. *A cut-off purchasing behavior with threshold price p^A refers to the function $D^A(p) = 1_{(0,p^A]} \times \varepsilon$*

In practice, what sort of behavioral intervention could lead to such a cut-off purchasing behavior? A consumer group or activists from an environmental NGO might decide to stop consuming a product when its price is deemed too high and they could set a clear threshold for that, as in the boycott movement analyzed in Hendel et al. [2017]. Other less radical initiatives could also generate a dramatic shift in demand around a limit price, such as a large price advertisement campaign or the display of a recommended retail price on the packaging of the product.

Theorem 1, the main theoretical result of this subsection, characterizes a threshold price p^{A^*} such that the corresponding cut-off purchasing behavior is optimal among all possible purchasing behaviors. In a nutshell, the proof goes as follows. First, Proposition 1 characterizes the optimal threshold price p^{A^*} that maximizes total consumption $D_2(p^2)$ among all cut-off purchasing behaviors. Then, Lemma 1 shows that this outcome is optimal among all possible demand function D_2^A. The formal proof of these results is available in the appendix, as well as that of Theorem 2, an extension of Theorem 1 to the case of n symmetrical oligopolists.

The determination of the optimal threshold price p^{A^*} is simple. Notice that when affected consumers adopt a cut-off purchasing behavior with a threshold price p^A below the initial price p_1, the firm faces an alternative : either it sets its price p_2 at the threshold price p^A so that affected consumer purchase the green good, or it sets its price p_2 above this threshold and affected consumers will not consume the good. In the latter case, the firm will set the price p^N defined below.

Definition 2. *The neutral price p^N is the price that would be set by the firm if the affected consumers were absent from the market. Equivalently, it corresponds to the equilibrium price p_2 when $D_2^A = D^N$.*

We have shown that the firm must choose between the prices p^A and p^N. If the firm finds it strictly more profitable to set the price p^A than the price p^N, an intervention with a slightly lower p^A would have increased the consumption of neutral consumers without changing that of affected consumers. This shows that, at the optimal threshold price p^{A^*}, the firm is indifferent between setting either of these two prices. Thus, the the optimal threshold price p^{A^*} is characterized by

$$\Pi^N(p^N) = \Pi^N(p^{A^*}) + \varepsilon(p^{A^*} - c)\ ,\ \ p^{A^*} \in [c, p^N]$$

Proposition 1 wraps up these ideas. I assume that Π^N is smooth, single-peaked in p^N and that D^N is decreasing on $[c, p^N]$.

Proposition 1. *There exists a unique price $p^{A^*} \in [c, p^N]$ such that the cut-off demand function with threshold price p^{A^*} makes the firm indifferent between (1) setting the price p^N to sell the product to some neutral consumers and (2) setting the price p^{A^*} to sell the products to more neutral consumers* *and all the affected consumers. It is characterized by*

$$\Pi^N(p^N) = \Pi^N(p^{A^*}) + \varepsilon(p^{A^*} - c)\ ,\ \ p^{A^*} \in [c, p^N]$$

The equilibrium demand under a cutoff demand with threshold price p^{A^*} is

$$D_2(p_2) = D^N(p^{A^*}) + \varepsilon$$

So far, we have only considered the case of cut-off demand functions. Lemma 1 shows that this class of demand functions is optimal among all possible demand function D_2^A (assumed to be asymptotically dominated by the inverse of the price so that the equilibrium price is well defined). Its proof is available in the appendices and relies mostly on the facts that D^N is decreasing and D_i^A is bounded by ε for $i \in \{1,2\}$. This leads us to the main Theorem :

Theorem 1 (Optimal purchasing behavior)**.** *The purchasing behavior $D_2^A = 1_{(-\infty, p^{A^*}]}$ maximizes $D_2(p_2)$ over all possible choices of D_2^A. Conversely, every optimal purchasing behavior D_2^A must be such that $p_2 = p^{A^*}$ and $D_2(p_2) = D^N(p^{A^*}) + \varepsilon$*

Note that Theorem 1 does not state that the optimal purchasing behavior is unique. Besides, one can easily construct an optimal purchasing behavior different from a cut-off demand function, for instance by starting from a cut-off function with threshold p^{A^*} and decreasing the demand in the $(0, p^{A^*})$ price range. However, any optimal purchasing behavior D_2^A must lead to the equilibrium price $p_2 = p^{A^*}$ and satisfy $D_A^2(p^{A^*}) = \varepsilon$.

Theorem 1 has a striking implication for behavioral intervention evaluation. Contrary to the common intuition, all optimal interventions are such that consumers stop right away to consume at the current price p_1 - since it is higher than p^{A^*}. A typical experimental evaluation measuring only the behavioral effect - the immediate consumption change before the price reaction of the firm - would thus dismiss any optimal intervention as strongly ineffective.

The theorem also provides a theoretical upper bound for the price and demand changes following a behavioral intervention. The next subsection will formalize this idea and derive tractable expressions related to the market conditions for the intervention effects .

2.3 Magnitude of the price and behavioural effects

In this subsection, I derive simple formulas for the magnitude of a price change following an intervention when the affected population is small. I focus on two important cases : optimal interventions - as defined in the previous subsection - and interventions that induce the same purchasing behavior no matter the size of the affected population.

I focus on the case of a small share of affected consumers. Indeed, most of the behavioral interventions that are actually implemented have a limited scale as compared to their relevant market. Marketing practices and nudges are usually decided and implemented by a single actor, be it a firm or some local public authority, hence cannot affect every consumer. Advertisements and environmental awareness campaigns on TV, radio or Internet target their audience to increase their cost effectiveness. Even mandatory product labeling is unlikely to be noticed, understood and actually used by more than a small fraction of the consumers. Note that the assumption here is not that the initial consumption is small, but that the change in demand triggered by the intervention takes place in a small population.

I will use the parameter ε introduced previously to account for the scale of the intervention. In the previous search for an optimal purchasing behavior, ε was an upper bound on D^A that could be interpreted as the share of affected consumers. More generally, a purchasing behavior D_i^A can be interpreted as the aggregate demand resulting from the purchasing behavior $\underline{D}_i^A$ being adopted by each individual in the mass ε of affected consumers. This leads to the following formula :

$$D_i(p) = D^N(p) + D_i^A(p) = (1-\varepsilon)\underline{D}^N(p) + \varepsilon \times \underline{D}_i^A(p)$$

Here, ε is the share of affected consumers and $1-\varepsilon$ that of neutral consumers. By extension, I introduce $\underline{\Pi}^N := \underline{D}^N(p)(p-c)$ and $\underline{\Pi}_i^A := \underline{D}_i^A(p)(p-c)$ the profit functions associated to one individual in each consumer group. Note that ε says nothing of how much the intervention alters the purchasing behavior of the affected consumers, it only restricts their number. When ε is small, so is the affected population as compared to the neutral population. In the extreme case where $\varepsilon = 0$, no consumer is affected by the intervention and the firm sets the price $p_1 = p_2 = p^N$ - which, by definition, is optimal for the neutral demand D^N.

Using a first-order approximation of the profit function of the profit function Π^N in the neighborhood of p^N and the previous characterization of the final equilibrium price $p_2 = p^{A^*}$ for optimal interventions, one can derive an equivalent of the price change when the population size is small.

Proposition 2. *[Optimal purchasing behavior] Under an optimal intervention - for instance, when D_2^A is a cut-off demand function with threshold price $p^{A^*}(\varepsilon)$ - we have*

$$\Delta p^* \underset{\varepsilon \to 0}{\sim} \sqrt{\frac{2(p_1 - c)}{\frac{\partial^2 \Pi^N}{\partial p^2}(p_1)}} \times \sqrt{\varepsilon}$$

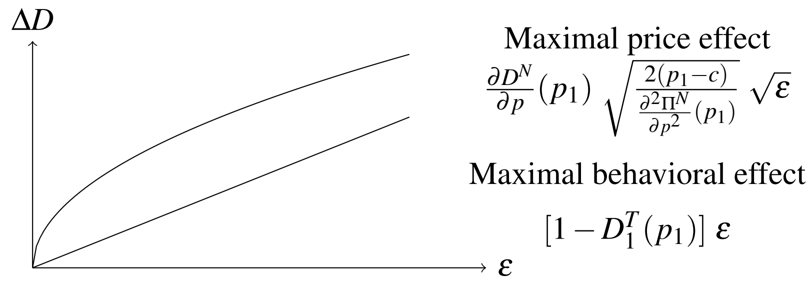
Proposition 2 shows that the price change - hence the price effect - following an optimal intervention goes as the square root of ε, the share of consumers affected by the intervention. Since the behavioral effect $D_2^A(p_2) - D_2^A(p_1) \leq D_2^A(p_2) \leq \varepsilon$ is at most linear in ε, this means that the price effect dominates. In other words, the most important driver of consumption change in small optimal interventions is the price effect, not the behavioral effect. This is illustrated in Figure 2.

Moreover, the previous result provides a tractable asymptotic upper bound for the price and demand change following a small-scaled intervention, which can be used to perform back-of-the-envelope estimations. In particular, the second-order derivative of the profit of the firm at current prices and its absolute margin on the green good seem to be the key determinants of this upper bound.

Proposition 3 (Interventions that induce the same purchasing behavior $\underline{D}_2^A$ no matter the size of the affected population)**.** *When $D_2^A = \underline{D}_2^A \times \varepsilon$ and $\underline{D}_2^A$ is smooth, we have*

$$\Delta p \underset{\varepsilon \to 0}{\sim} \frac{\frac{\partial \underline{\Pi}_1^A}{\partial p}(p_1) - \frac{\partial \underline{\Pi}_2^A}{\partial p}(p_1)}{\frac{\partial^2 \Pi^N}{\partial p^2}(p_1)} \times \varepsilon$$

The case of interventions that induce the same purchasing behavior $\underline{D}_2^A$ no matter the size of the affected population is also very relevant for applications. Many behavioral interventions are designed and evaluated without anticipating the scale at which they will be deployed or the share of consumers that they will actually be able to reach. Proposition 3 shows that the price change is linear in ε and in particular, asymptotically negligible as compared to the optimal case. This shows that interventions designed or evaluated independently of the scale of their deployment are inherently limited, as their price effect is bound to be at most linear.



Notes: The behavioural effect is at most linear in the share ε of treated consumers. The optimal price effect goes as $\sqrt{\varepsilon}$. Therefore, for ε small, the latter dominates the former.

Figure 2: Comparing the magnitude of the behavioural effect and price effect

The price change - hence the price effect - following such an intervention depends on the difference between the profit gradient of the affected demand before and after the intervention. This implies that the characteristics of the affected population - i.e. D_1^A - can affect significantly the magnitude of the price effect. In order to maximize it, the intervention should target consumers whose corresponding profit function is upward-sloping at current price. Assuming that Π_1^A is single-peaked, this means that the monopoly price for this consumer group is higher than the initial equilibrium price. In particular, this suggests that consumers with either a high willingness to pay for a green product or those with a low price sensitivity are suitable targets.

TO conclude this theoretical section, I have shown that 1) the most effective behavioral interventions induce a positive price effect, 2) the price effect dominates the behavioral effect in small interventions and 3) optimal behavioral interventions make consumers extremely sensitive to prices. In the next sections, I will test these ideas using actual market data.

3 Methods

In the rest of the paper, I will compare changes in green consumption induced by two types of interventions : (A) interventions raising consumer willingness to pay for the green good and (B) interventions raising the price sensitivity. Here, I am confronting a classical approach focusing on the WTP to my theoretical conclusion that making consumers more price-sensitive could be beneficial overall. This approach is more restrictive in the type of interventions considered than in the previous section, but it relies on a realistic structural model for the demand and supply informed by market data.

My methodology to simulate behavioral interventions is novel, but likens Villas-Boas et al. [2020]. I first estimate separately the willingness-to-pay for the green good and the price sensitivity at the household-level by calibrating a structural demand model. Then, I introduce behavioral interventions as changes in these two parameters affecting a specific subsample of consumers. To complete the simulation, one must compute the new price equilibrium after this change in demand. The demand and supply model follow the standard practice in empirical industrial organization.

This approach is applied to panel data on organic egg consumption in non-specialized food retail in France. I take organic eggs as the green good and ask which interventions maximize their consumption. Eggs is the food category for which organic products have the largest market share in France [Bio, 2020]. The consumer panel is representative of the French population in 2012, a period at which organic egg consumption was still niche.

In this section, I start by presenting the data, then the demand model, the supply model and finally the simulations, each of these four steps building on the previous ones.

3.1 Data

My empirical analysis is based on home-scanned egg purchase data for the year 2012 from a consumer panel (Kantar WorldPanel) representative of French households. The panelists have to scan the bar-code of the purchased products after each shopping trip, providing reliable information of the characteristics of their purchase. In particular, we know the brand, label, calibre and number of eggs in the box. I distinguish between three egg labels : battery hens, free-range hens and organic hens. We focus on eggs having medium (M) or large (L) calibre, sold under one of top three national brands or a retailer own brand. I define a "simplified brand" variable by grouping together retailer own-brands with a similar range (top range, middle range and low range), and national brands in a forth group. I work with a total of 115 different products.

The panelists must also report what store they went to. We limit the sample to non-specialized food stores, which accounted for 64% of organic eggs purchases in France in 2019 and more generally half of the sales of organic products in 2012 according to the French agency for organic food [Bio, 2020]. Since the central procurement service can be retrieved from the product barcode, I define a retailer as a pair formed by a central procurement service and a store format, so as to distinguish for instance convenience stores and hypermarkets from the same chain. I find 14 retailers in total, which is consistent with previous studies on the French retail industry [Allais et al., 2015a].

Non-purchasing is considered as a product of utility zero that is always available to the consumer. The shopping trips that led to no egg purchase are key in the identification of the utility derived from egg consumption. It is difficult in all generality to disentangle non-purchase due to some dissatisfaction with respect to the current offer from non-purchase due to an egg stock at home. Making use of the limited time eggs can be stored, the shopping trips included in the final sample are selected as follows. First, I draw randomly one shopping trip involving the purchase of eggs per four-week period and household, if any. Then, for periods during which no egg purchase was made, I draw at random one empty shopping trip during the period. Thus, I make sure that the observed decision not to purchase egg is never driven by an sufficient stock at home.

The identification of household-specific parameters requires a minimal number of observations. Therefore, I consider only households that have purchased eggs during at least 6 periods out of 13. Moreover, I use two available demographic variables : the quartile of the household in the distribution of income as well as its position over the life cycle - split in ten categories, depending on the composition and age of the members of the household. Figure 1 illustrates the characteristics of the final sample of $N = 2572$ households.

Finally, estimating a multinomial logit model requires the definition of an appropriate choice set for each shopping trip. Starting from the set J_{rt} of products sold by retailer r during period t, I define the set J_{it} of products available to household i during period t as the union of the J_{rt} for several retailers r. The choice of this list of retailers affects the level of competition assumed in the model. The larger the number of retailers included in the list, the less captive consumers are, the higher the competitive pressure on retailers. On the one hand, if we use the union over all retailers, we consider that household i could have equally chosen to purchase eggs at any other retailer. This assumption ignores the constraints of limited retailer availability and transportation costs, as it is unlikely that the choice to visit a given retailer is entirely driven by the price and characteristics of their eggs only. On the other hand, if $J_{it} = J_{ir}$ where r is the retailer that was indeed visited at period t, then we are taking the choice of a visited retailer as entirely independent to the price and characteristics of their eggs. This may be too strong an assumption. In order to build realistic choice sets, I take the union over all retailers that the household visited during the year 2012, so as

Socio-demographic variable	Frequency
Life cycle	
Couple (under 35 y.o.)	0.214
Couple (between 35 and 65 y.o.)	0.168
Couple (over 65 y.o.)	0.136
Family (eldest child under 5 y.o)	0.080
Family (eldest child between 6 and 11 y.o.)	0.100
Family (eldest child between 12 and 17 y.o.)	0.120
Family (eldest child between 18 and 24 y.o.)	0.127
Single (under 35 y.o.)	0.019
Single (between 35 and 65 y.o.)	0.111
Single (over 65 y.o.)	0.116
Income quartile in the French population	
First quartile	0.135
Second quartile	0.414
Third quartile	0.309
Fourth quartile	0.142
Total sample: N = 2572 households	

Table 1: Summary statistics of the household sample

to make sure that retailers in the list could indeed be considered by the household.

3.2 Demand model

This section introduces the structural model used to estimate consumer demand, providing details on how it deals with price endogeneity and household heterogeneity. The demand for eggs is modeled by a multinomial logit with random coefficients α_i for the price sensitivity and β_i for the valuation of the organic attribute. Appendix B gives the general expression of the likelihood function and the demand elasticities for this class of models. The structural equation of the random utility model writes :

$$U_{ijt} = \gamma \cdot \mathbf{x}_j - \alpha_i \times p_{jt} + \beta_i \times \text{IsOrganic}_j \times \text{BuysOrganic}_i + +\delta \times v_{jt} + u_{ijt} \tag{2}$$

The vector $\mathbf{x}_j$ stands for the egg characteristics, except that of being organic. The effect of being organic appears through the term $\text{IsOrganic}_j \times \text{BuysOrganic}_i$. While IsOrganic_j is a binary variable that indicates whether the egg is organic, the variable BuysOrganic$_i$ indicates whether household i has purchased organic eggs at least once in 2012. Because of the interaction between BuyOrganic$_i$ and β_i, the latter can be interpreted as the valuation for organic eggs among those that sometimes purchase organic eggs. Noise terms u_{ijt} follow a standard Gumbel and are mutually independent. Note that the price is the only product characteristic that depends on the time period.

The term v_{jt} is a control function for the endogeneity of prices [Train, 2009]. It corrects the bias induced by the correlation between price variations and unobserved determinants of purchase decision. For instance, special offers on a product often combine low prices with more visibility at the point of sales, which increases the probability of purchase. The control function is nonzero only for products that have been bought and is equal to the residual of the following regression

$$p_{jt} = \psi \cdot \mathbf{x}_j + \phi \cdot \mathbf{z}_j + v_{jt} \tag{3}$$

The purchase price is instrumented - as often in the literature [Nevo, 2000, Allais et al., 2015b] - by the characteristics of the products and the average price of a similar product at competitors. Thus, in Equation 2, the price variable used is not directly the price p_{ijt} paid by the consumer - which is only available for the purchased product - but its average p_{jt} for the same product at this retailer during period t. This definition applies to all the products available in the choice set.

The random coefficients α_i for the price sensitivity and β_i for the valuation of the organic label are random variables with one realization per household. Because of the factor BuysOrganic$_i$ in the structural equation, the distribution of β_i is identified only on households that have purchased organic eggs at least once in the year, and β_i is otherwise assumed to be zero. I make this modeling choice for two reasons. First, because it is difficult to identify the valuation of an attribute that is rarely included in the consideration set of the consumers. Second, because the method to retrieve household-level valuation for the organic label presented in the next paragraphs makes little sense for households that never purchase organic eggs.

The model is estimated assuming a joint normal distribution of the coefficients α_i and β_i in the population. Their means $(\bar{\alpha}, \bar{\beta})$ are assumed to be income-group-specific whereas the variance covariance matrix Σ is shared across income groups. Hence the following equation, where w_i

follows a two-dimensional standard normal distribution

$$(\alpha_i, \beta_i) = (\bar{\alpha}, \bar{\beta}) \cdot \mathbf{d}_i + \Sigma\, \mathbf{w}_i \tag{4}$$

Estimating the model tells us what the distribution of α and β is at the aggregate level, but says nothing of its value at the household-level. To do so, I determine α_i^{BAYES} (resp. β_i^{BAYES}), the expectation of the Bayesian posterior mean for α (resp. β) conditionally on household i's observed purchase decisions $purchase_i$ and the parameters $\theta_{\text{LN}} = (\bar{\alpha}, \bar{\beta}, \Sigma)$ of the population distribution for (α, β). As mentioned previously, I assume $\beta_i = 0$ for households that have never purchased organic eggs in the year, consistently with the estimated demand model. The general analytical expression for the expectation of the Bayesian posterior mean is reminded in Appendix C.

$$\begin{cases} \alpha_i^{\text{BAYES}} & = E(\ \alpha_i \mid d_i, \bar{\alpha}, \bar{\beta}, \Sigma, \text{purchase decisions for household } i\ ) \\ \beta_i^{\text{BAYES}} & = E(\ \beta_i \mid d_i, \bar{\alpha}, \bar{\beta}, \Sigma, \text{purchase decisions for household } i\ ) \end{cases} \tag{5}$$

The demand $D_{ij}(\mathbf{p})$ of household i for product j is assumed to be equal to the market share as predicted by Equation 2 when the constant α_i^{BAYES} has been substituted to the random variable α_i. Therefore, at the household-level, the demand model is assumed to be multinomial logit - without random coefficient. The aggregate demand $D_j(\mathbf{p})$ for product j is just the finite sum of all the household-level terms $D_{ij}(\mathbf{p})$.

3.3 Supply model

Each retailer r sells a set J_r of products, product j having a marginal cost c_j and being sold at a price p_j. Given the vector $\mathbf{p}$ of prices and the VAT tax rate $\tau = 5.5\%$, its profit writes

$$\Pi_r = \sum_{j \in J_r} D_j(\mathbf{p})([1-\tau]p_j - c_j)$$

Retailer r's program consists in setting its tax-inclusive prices $(p_j)_{j \in J_r}$ so as to maximize its profit Π_r. The first-order optimality condition with respect to the price of product $j \in J_r$, denoting $D_k(p)$

the aggregate demand for product k writes

$$D_j(\mathbf{p}^*) + \sum_{k \in J_r} \frac{\partial D_k}{\partial p_j}(\mathbf{p}^*) \ ([1-\tau]p_k^* - c_k) = 0 \tag{6}$$

With matrix notations, the first-order condition for each product can be grouped as

$$\mathbf{D}(\mathbf{p}^*) + \blacksquare(\mathbf{p}^*)([1-\tau]\mathbf{p}^* - \mathbf{c}) = 0 \text{ avec } \blacksquare = \left(1_{J_r}(k) \times \frac{\partial D_k}{\partial p_j}(\mathbf{p}^*)\right)_{(j,k)\in J^2} \tag{7}$$

In the previous equation, marginal costs can be identified from the price, demand and demand elasticities at equilibrium. Once the demand model has been estimated , it is possible to compute

$$\mathbf{c} = \blacksquare(\mathbf{p}^*)^{-1}\mathbf{D}(\mathbf{p}^*) + [1-\tau]\mathbf{p}^*$$

Since price and demand fluctuate over the year, marginal costs are computed using data from an arbitrary period - period 11. The demand model is fundamentally a model of variety choice, but its predictive power regarding quantity is quite limited. In order to focus on the choice between egg variety, I remove the shopping trips that led to no purchases from the data and the possibility for households not to purchase during a shopping from the model. This means that the predicted market shares used here for retrieving marginal costs and later for simulating behavioral interventions are conditional on the fact that the household purchases.

As explained earlier, the demand model **D** used here is a sum of household-specific multinomial logit predictions and not the direct predictions from the initial random coefficient multinomial logit model. In particular, price elasticities are just the sum of household-specific elasticities that have a very tractable expression since the model does not involve a random coefficient - see Appendix B.

3.4 Intervention simulations

Using the previously described demand and supply model, I perform some policy simulations. Let me clarify how interventions are defined and simulated.

From the estimation of the demand model, I have retrieved two household-level determinants of the purchasing behavior: the price sensitivity α_i and the utility β_i derived from the organic label. In order to simulate behavioral interventions, I change the value of these parameters in the affected population and compute the new market equilibrium. In this approach, an intervention can be specified as a set of affected consumers and the transformations f and g that are applied respectively to the parameters α_i and β_i.

$$(\alpha_i, \beta_i) \text{ for } i \in \text{Consumers} \underset{\text{Intervention}}{\longrightarrow} \begin{cases} (f(\alpha_i), g(\beta_i)) & \text{if } i \in \text{Affected Consumers} \\ (\alpha_i, \beta_i) & \text{if } i \in \text{Passive Consumers} \end{cases}$$

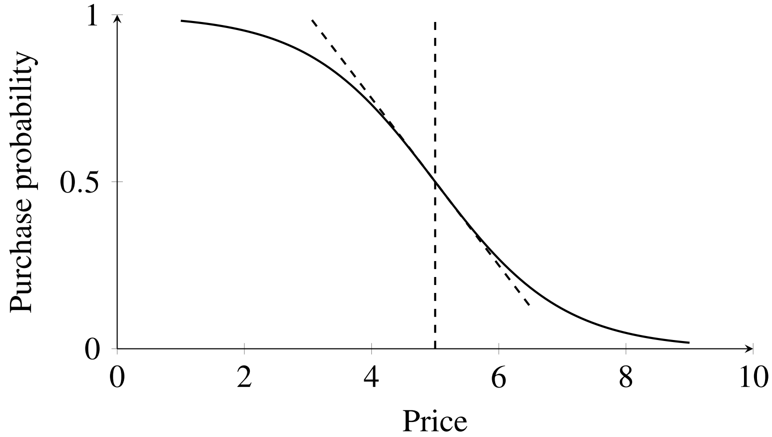
The decision whether or not to purchase organic eggs in a logit model is more easily understood in terms of price sensitivity α_i and willingness-to-pay WTP_i for an organic egg.

$$\text{WTP}_i = \frac{\gamma_{\text{Standard egg value}} + \beta_i}{\alpha_i}$$

The willingness-to-pay is the ratio of the utility of an organic egg by the utility α_i of money. It can be interpreted as the price that makes the consumer indifferent between purchasing a standard organic egg and not purchasing. Figure 3 illustrates how a change in WTP_i and α_i affects the probability of purchasing an organic egg depending on its price.

Let me explain in detail what happens in two important cases. A "pure increase in WTP", meaning an increase in WTP_i holding α_i constant, entails that β_i is increasing. The willingness to pay for organic eggs increases and that for non organic egg remains constant. We know that the direct effect on the consumption of affected consumers will be an increase in the share of organic consumption and an increase in egg consumption overall. Similarly, a 'pure increase in price sensitivity", meaning an increase in α_i holding WTP_i constant, also entails that β_i is increasing. The willingness to pay for organic eggs does not change and that for non organic eggs decreases. We know that the direct effect on the consumption of affected consumers will be an increase in the share of organic consumption and an decrease in egg consumption overall.

On the (α_i, WTP_i) plane, a pure increase in price sensitivity moves households to the right while a pure increase in consumer WTP moves them to the top. Figure 7 in the appendix illustrates several transformations that implement these two cases. In my baseline simulations, I use "Reaching a target price sensitivity" and "Reaching a target WTP", as they have the intuitive implication that



Notes: The willigness to pay is the price at which the consumer is indifferent between consuming and not consuming The price sensitivity is the slope of the demand curve at the willigness to pay. Raising the willigness to pay means shifting the demand curve to the right. Raising the price sensitivity somehow rotates the demand curve clockwise. Note that the limit when the price sensitivity goes to the infinite is a cut-off demand function with threshold price the willingness to pay.

Figure 3: Willigness to pay and price sensitivity under a logit demand

the intervention would uniformize the behavior of affected consumers regarding the dimension of interest. Their effect is on household demand is illustrated in the appendix in Figure 7.

$$(\alpha_i, \text{WTP}_i) \text{ for } i \in \text{Consumers} \underset{\text{Intervention}}{\longrightarrow} \begin{cases} (f(\alpha_i), g(\text{WTP}_i)) & \text{if } i \in \text{Affected Consumers} \\ (\alpha_i, \text{WTP}_i) & \text{if } i \in \text{Passive Consumers} \end{cases}$$

$$\text{with } \begin{cases} f(x) = \max(x, \alpha_{\text{Target}}) \text{ and } g(x) = x & \text{for "Reaching a target price sensitivity"} \\ f(x) = x \text{ and } g(x) = \max(x, \text{WTP}_{\text{Target}}) & \text{for "Reaching a target willingness-to-pay"} \end{cases}$$

The values of the target price sensitivity and willingness-to-pay in the baseline simulations are $\alpha_{\text{Target}} = 40$ and $\text{WTP}_{\text{Target}} = 0.6$. A price sensitivity of $\alpha = 40$ correspond to the top of the initial price sensitivity distribution, where the median price sensitivity in the population is $\alpha = 23$. To understand what a willingness to pay for organic eggs of 60 cents implies, consider the case of a consumer that has the choice between purchasing organic eggs at 41 cents and free-range eggs at 29 cents (the average market prices). Given my estimated demand model, with a WTP of 60 cents for organic eggs, this consumer would favor them more than 99% of the time. These parameter choices are extreme but also perform a wide range of robustness checks with smaller parameter values.

I still need to specify the population of affected consumers. In my baseline simulations, I focus on the 1% consumers that are initially the least price sensitive. Figure 4 illustrates where these consumers are located on the (α_i, WTP_i) plane. Proposition 3 of the theoretical model predicts that the potential of an intervention will be larger for this consumer group. An affected population of 1% is a realistic figure, comparable to the share of households involved in the boycott described in Hendel et al. [2017]. As a robustness check, I also consider consumers that are the most willing to pay for organic products and test an affected population size of 3%. This is a very conservative choice, for two reasons. First, Proposition 2 implies that the price effect of an optimal intervention is smaller relatively to the behavioral effect for larger populations. Second, the greenest consumers are probably the easiest to convince to adopt a behavior that maximizes an environmental outcome.

Once the demand from the affected population has been changed, a new price equilibrium is computed. To do so, I use a classical iterative algorithm from the literature, detailed in the appendix. I then report the total effect of the intervention on organic consumption, accounting for the supply-side reaction.

4 Results

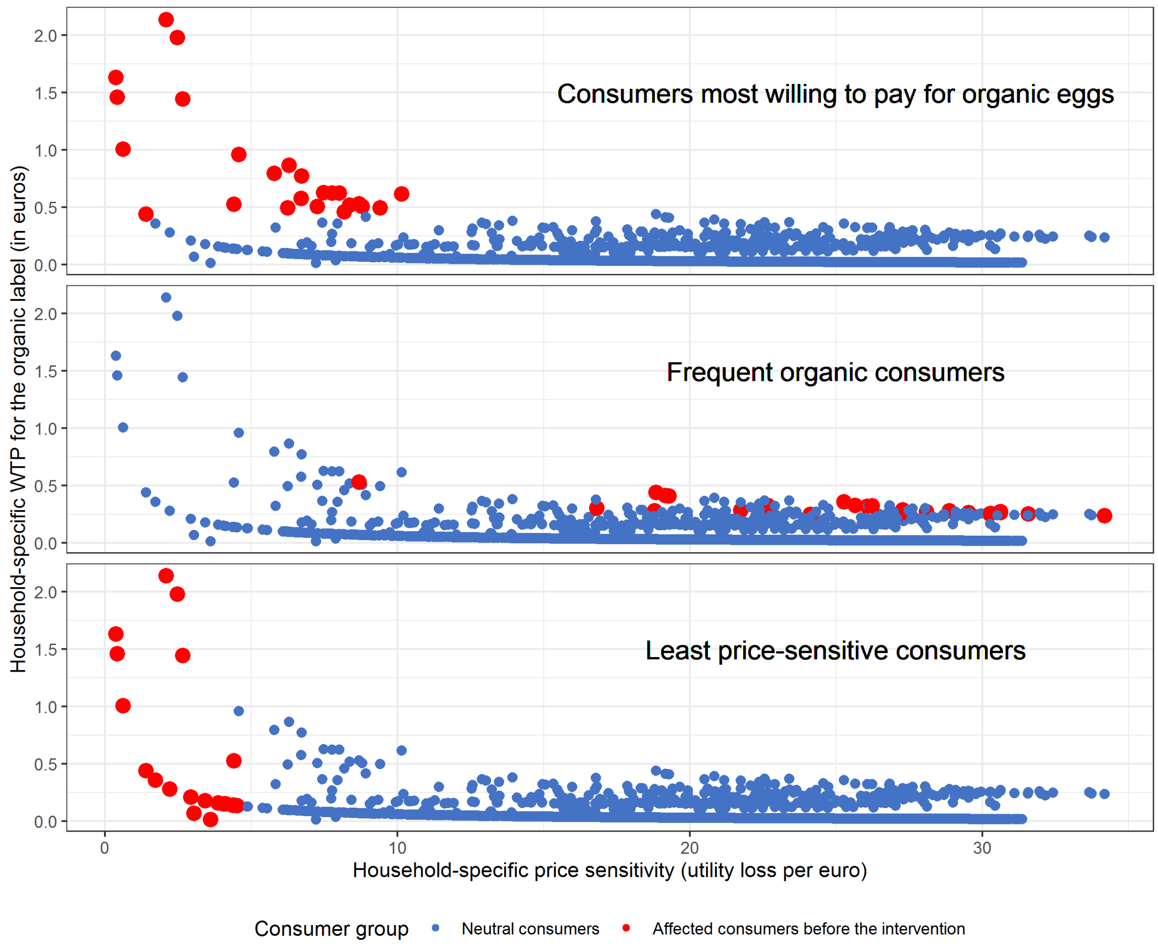
4.1 Estimated demand

Figure 2 shows the estimated parameter values for the demand model, as well as the predicted utility attributed by a reference household to each egg characteristic - normalized by the price sensitivity, so that each value can be interpreted as being expressed in euros. The sign of the estimated utilities are as expected for calibre, label and consumer own-brand range. More surprisingly, national brands are barely more valued than bottom-range own-brands. This could be due to the use by retailers of communication or shelf-filling practices that are more favorable to their own products. At the aggregate level, one can also notice that price sensitivity is logically higher for lower income groups.

Variable	Coefficient	Monetary Value
Label		
No Label	Reference	0.000€
Free-range label	1.325*	0.059€
Organic label (random coefficient average)	3.943*	0.176€
Simplified brand		
Low-range own brand	Reference	0.000€
Medium-range own brand	0.683*	0.031€
High range own brand	1.483*	0.066€
National brand	0.314*	0.014€
Calibre		
Medium	Reference	0.000€
Large	0.261*	0.012€
Price sensitivity		
Income Q1 (random coefficient average)	-23.716*	
Income Q2 (random coefficient average)	-22.417*	
Income Q3 (random coefficient average)	-20.522*	
Income Q4 (random coefficient average)	-19.759*	
Variance and covariance		
Standard deviation (price sensitivity)	6.633*	
Standard deviation (organic label)	1.711*	
Correlation (price sensitivity and organic label)	1.133*	
Control variable		
Control variable	6.471*	

Notes: The coefficients reported are the fixed effects for the characteristics of the products, the parameters of the joint distribution of the random coefficients and the coefficient for the control function. The price sensitivity distribution has an income-quartile-specific average, but a shared standard deviation. The average and standard distribution of the willingness to pay for the organic label are estimated only on the consumers that have ever purchased organic. The monetary value of the fixed effects for product characteristics are obtained by dividing the value of the coefficient by the average price sensitivity for the second income quartile (serving as a reference point for the utility of money). The * indicates that the coefficient is significantly different from zero at the 5% level.

Table 2: Calibration of the demand model



Notes: Each household corresponds to a point in the (willigness to pay, price sensitivity) plane. The effect of the behavioral interventions is to move a fraction of these households elsewhere in this plane. The fractions of households considered in the simulations are represented in red. The most willing to pay are logically the uppermost points and the least price-sensitive the leftmost. The position of the most frequent organic consumers is an empirical fact.

Figure 4: Affected consumer groups tested in the simulations

4.2 Household-level heterogeneity

Figure 4 illustrates the joint distribution of the mean Bayesian posteriors in the $(\alpha_i, \mathrm{WTP}_i)$, highlighting several relevant consumer groups that will be later used as affected population in the intervention. Notice that the curve at the bottom correspond to households that never purchased organic eggs and have been attributed a value of zero for β. It is not a line but a curve because we are working with $(\alpha_i, \mathrm{WTP}_i)$ instead of the (α_i, β_i) plane.

Category	Price	Marginal Cost	Marginal Benefit
Cross product average	0.272	0.197	0.076
Label			
No Label	0.184	0.123	0.061
Free-range label	0.291	0.215	0.076
Organic label	0.417	0.311	0.106
Simplified Brand			
Low-range own brand	0.148	0.090	0.058
Medium-range own brand	0.228	0.164	0.064
High range own brand	0.273	0.193	0.080
National brand	0.333	0.247	0.087
Format			
Hypermarkets	0.252	0.180	0.072
Supermarkets	0.278	0.200	0.077
Convenience stores	0.302	0.221	0.081
Junior department stores	0.332	0.249	0.083

Notes: Prices are directly observed in consumer panel data. Marginal costs are retrieved when calibrating the supply side model. Marginal benefits are the difference between average prices and marginal costs. All the numbers are in euros. Each rows contains the average price, marginal cost and marginal benefit for the products having the characteristic mentioned in the Category column.

Table 3: Calibration of the supply model

4.3 Retail marginal costs

Figure 3 illustrates variations in marginal cost and marginal benefit across labels, simplified brands and store format, under different competition assumptions. The marginal costs estimates vary as could be expected along these categories.

The model suggests that retailers enjoy a larger marginal benefit on organic eggs than for other labels, validating the niche pricing hypothesis. The difference in retrieved retail marginal costs between organic and free-range are not that far from those for their agricultural production given by experts [ITAVI, 2017]. However, the large difference in marginal costs between free-range and battery eggs is difficult to reconcile with this alternative data source.

4.4 Simulations

Using my calibrated model, I simulate behavioral interventions that make consumers more willing to pay for organic eggs (A), make them more sensitive to prices (B) or do both (AB). Then, I check the sensitivity of the results to the way the interventions are specified.

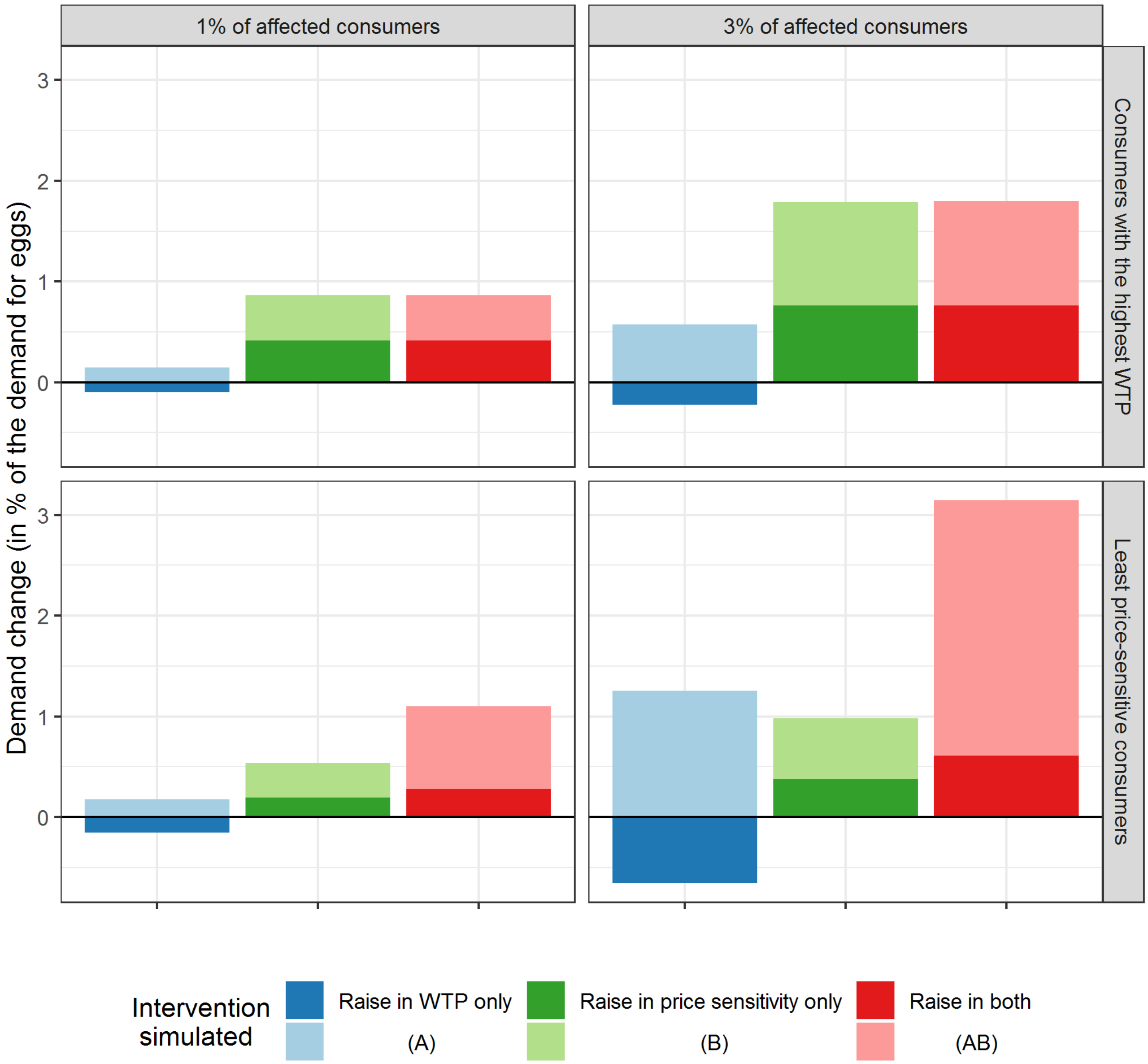
Figure 5 gives the simulation results for the baseline specification of the intervention.

For the simulated interventions, it is clear that what performs best is (AB) a raise in both price sensitivity and in willingness to pay for the organic label, followed by (B) a pure raise in price sensitivity. In order to analyze the results, notice that the price effect corresponds to the darker bars on the figure. When the simulated intervention is (A) a raise in WTP, the price effect is negative. Even if the overall effect on green consumption is positive, it happens only through an increase in consumption among affected consumers and causes an almost comparable decrease among unaffected consumers. In contrast, the price effect is positive for the two other interventions types (B) and (AB).

The difference in results between the two consumer segments is also instructive. Increasing consumer WTP (A) seems to perform better when the intervention targets consumers with a low price sensitivity. Since those consumers rarely purchase organic eggs before the intervention, there is more room for improvement among affected consumers. However, due to their low price sensitivity, their increased WTP for organic eggs leads to higher organic prices that with the other consumer segment, which magnifies the negative price effect. Although (A) might be slightly more effective at increasing organic consumption than (B) in some settings, its distributional consequences are more controversial. It contributes to the polarization of organic consumption - higher for affected consumers, lower for others - by pushing prices up.

The magnitude of the price effect is half that of the intervention when it affects consumers with a high WTP for the green good, and a fourth of it when it affects consumers with a low price sensitivity. Therefore, it cannot be ignored when designing or evaluating interventions that are likely to affect mostly one of these two consumer segments.

The presence of a positive behavioral effect for (B) pure raises in price sensitivity might seem surprising. This is due to the way "holding willingness to pay" constant has been defined in section 3.4. When the price sensitivity is increased, I also increase the valuation of the organic attribute so that the willingness to pay for a medium organic egg remains constant. Since no such increase in



Notes: The dark bar indicates the price effect and the light bar indicates the total effect (i.e. the sum of the price and behavioral effects). In the case of an intervention raising the price sensitivity only (B) among the 3% of the consumer that have the highest WTP (green bars in top right corner), the price effect is around 0.8% and the total effect around 1.8%. In the case of an intervention raising the price sensitivity only (B) among the 3% of the consumer that are the least price sensitive (blue bars in top right corner), the price effect is negative (close to -0.7%) while the total effect is positive (around 1.2%).

Figure 5: Simulations results

valuation happens for non-organic eggs, the willingness to pay for them is reduced and this makes affected consumer more likely to choose organic eggs over other types of eggs. Still, this behavioral effect cannot be larger than size of the affected population times the market share of non-organic eggs among affected consumers before the intervention.

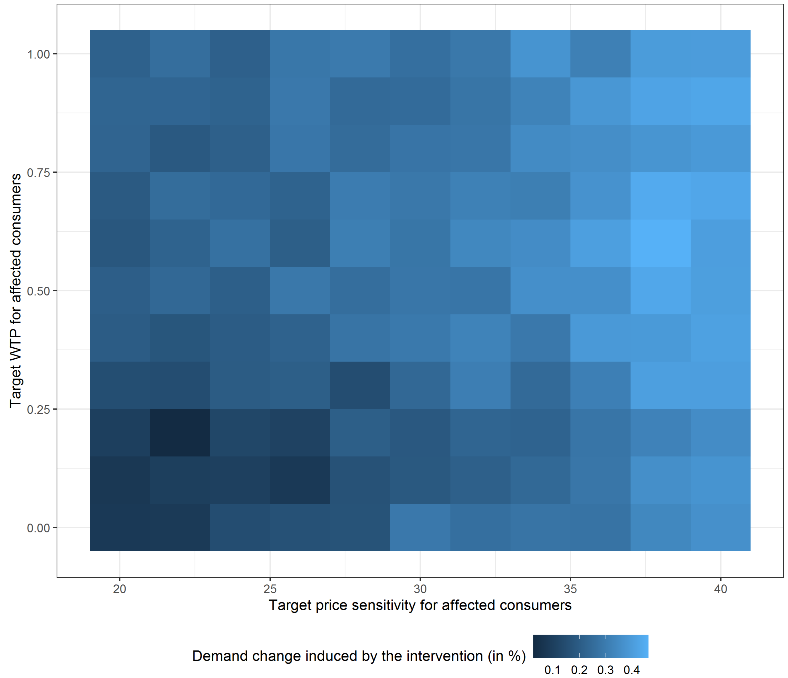
Therefore, the most important message from the figure is not that the total demand change is always higher when raising price sensitivity (since its behavioral part is debatable as it depends on technicalities on how the intervention is modeled) but rather that the price effect can be of comparable magnitude to the upper bound of the behavioral effect (which depends only upon the affected population, regardless of the simulated intervention). For the interventions considered in Figure 5, the ratio of the positive price effect to the upper bound for the behavioral effect in interventions (B) and (AB) varies between one to two and one to four.

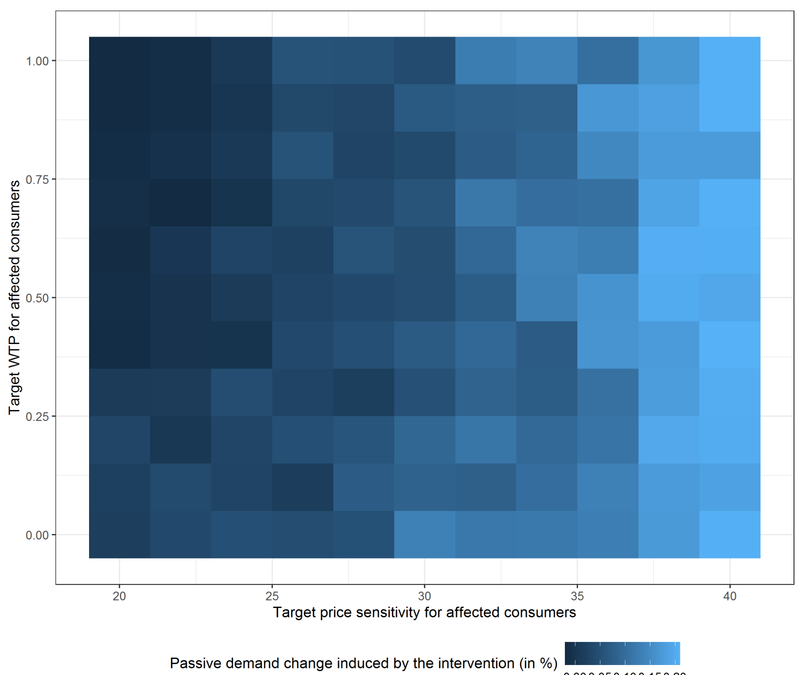
Since Figure 5 contains the simulation results for only a few values of the intervention parameters, I could have missed an interesting parameter value. I will perform the same simulation with a wide range of parameter values. Before moving to the results in Figure 6, let me discuss how the range of tested parameters has been chosen.

First, notice that above a certain level, raising consumer WTP makes no difference in terms of affected demand and translate only into higher prices, hence a lower total demand. In particular, this is the case once the market share of organic products among consumers after the intervention is close from 100%. This criterion is met with the parameter value tested above. Therefore, there is no need to consider higher WTP parameter values.

Second, it would be indeed highly interesting to test the case of extremely price-sensitive consumers. However, if the shape of the demand curve changes brutally, first-order condition in the algorithm that computed the price equilibrium may face some numerical issues. Using alternative algorithms could cope with this issue, but would be very computationally demanding. Therefore, I do not consider interventions that bring consumer price sensitivity higher than 40 (utility loss per euro). As mentioned above, a price sensitivity of 40 is already slightly above the highest price sensitivity observed in the data.

Third, it makes no sense to consider negative parameter values. In the "Shift" case, this amounts to reducing - as opposed to raising - consumer WTP and price sensitivity. In the "Target" case, this means that the transformation has no effect on affected consumers. Overall, we have restricted our





Notes: Each tile corresponds to a value of the parameters α_{Target} and β_{Target}. The color reflects the result of the corresponding simulation, with lighter tiles indicating a larger increase in demand. The top heatmap reports the total effect, the bottom heatmap the effect on passive consumers only.

Figure 6: Sensitivity of the results to the intervention parameters α_{Target} and β_{Target}

analysis to a bounded set of intervention parameter values. Figure 6 displays the simulation results as heat maps in the space of parameter values in the "Target" case when the affected population is the 1% most frequent organic consumers.

On the heat maps, the lighter the tile, the more effective the intervention. It is clear than the best results in terms of total demand change are obtained with the highest price sensitivity targets. This is consistent with the theoretical model, as a higher price sensitivity means a steeper demand curve. In contrast, increasing further consumer WTP when it is already above the initial market price (roughly 0.4) does not seem to have any effect.

The heat map showing the change in passive demand illustrates a phenomenon that cannot be observed if we focus on the total price effect : the higher the WTP in the affected population, the smaller the change in consumption among non affected consumers. Our previous remark that total consumption stops raising with affected raising consumer WTP above a certain level can be explained by two compensating forces : while affected consumers get closer to consuming organic all the time, they also push prices up, which discourage organic consumption among passive consumers. Therefore, raising consumer WTP might just push some consumer groups to consume more often organic at the expense of other consumer groups.

To summarize, I have performed simulations with various specifications of the behavioral interventions and considered plausible consumer segments that could be affected. I have found that making consumer willing to pay more induces a negative price effect and can be quite inefficient in increasing green consumption, in particular when affected consumers already have a high willingness to pay for the green good. In comparison, making consumers more sensitive to prices works much better. The effect is always at least as good when the two policies are combined, as the increased price sensitivity prevents an opportunistic price reaction on the retailer side.

5 Discussion

This paper does not account for vertical relations. One may wonder to what extent a decrease in the price of the green good may have negative implications for the profit of green producers/manufacturers. This may lead to less investment and expansion in the green sector and be detrimental on the long-run to green consumption. The previous rationale relies on the assumption that there is a relation between retailers' and producers/manufacturers' margins. In the case of organic eggs, as for most homogeneous food products involving few processing steps, there are reasons to believe that retailers, not producers, capture most of the value. Major retailers group together to form even larger central procurement services that have a high market power and are able to purchase food products at a lower price [Molina, 2021]. Thus, in absence of powerful brands - as for the soda industry - or a highly concentrated upstream industry - as for the French milk product industry studied in Bonnet and Bouamra-Mechemache [2016], it can be expected that most of the margin will be captured by retailers. The results of the paper are applicable to a wide range of environmentally-relevant food industries - legumes, fruits and vegetables, staple food - as long as the previous criteria are met.

The main message of the paper is that communicating about the merits of a product without mentioning its price or production cost is not the best way to support its consumption in retail markets. Organic consumption is only one setting out of many where this rationale applies: the same goes for fruits and vegetables under a "5-a-day"-like public health campaign, food items with a better Nutri-score or ranked high by barcode scanning apps.

More generally, the paper has implications for the design and evaluation of behavioral interventions affecting the consumption of a good priced by a strategic agent. The theoretical model stresses the importance of thinking beyond experimentally-measured average treatment effects in order to anticipate the firm price response to the intervention. In particular, one striking consequence of the theoretical model is that optimal interventions require that affected consumers stop purchasing at current prices, which means that the average treatment effect of the intervention on sustainable consumption at current prices is negative. Besides, the theoretical upper bound for the magnitude of the price effect derived from the model provides a practical rule of thumb to test the relevance of the price effect for a given market and intervention.

Can we extend the rationale to other green goods that are crucial for the environmental transition, such as electric vehicles (EVs) ? It is probably fair to say that EVs are still in a niche market situation in many Western countries that resembles the one of organic eggs in France in 2012. One difference is that eggs have few other relevant characteristics than the label, whereas cars may have numerous other features that play an important role in the purchase decision. For instance, EVs are extremely vertically differentiated, ranging from SUVs or semi-autonomous vehicles to small cars with a very limited autonomy. In this context, the relevant supply-side decision is less price-setting than product design (how should EVs be positioned vertically). This latter topic was also discussed theoretically in Johnson and Myatt [2006] from the perspective of the firm. From an environmental perspective, the implications for behavioral interventions about EVs are that messages targeting more environmentally-aware or less price-sensitive consumers should go beyond the mere emissions of the vehicle and stress the fact that demand for luxury EVs may be detrimental to a wider development of the market. However, this rationale may not be fully applicable here, because of the dynamic interplay between product design and innovation and the existence of a secondary market for cars.

The model also has implications for environmental justice. The widespread use of consumption-based greenhouse gas emissions accounting - based on product-level life cycle assessment - to attribute environmental responsibility to consumers totally ignores the price effect. Therefore, this approach underestimates greatly the extent to which green price-insensitive consumers could further support green consumption, hence their potential for action. Being well-informed and careful regarding green product prices could contribute to environmental objectives more than accepting to pay a disproportionate price for these items. The distribution of sensitivity to prices in the population being quite different from that of income, this has also implications for the literature linking inequalities and demand-side mitigation policies.

6 Conclusion

In this paper, I argue that prices matter for the design and evaluation of behavioral interventions - labeling schemes, environmental information campaigns - promoting the purchase of greener goods in imperfectly competitive retail markets. Raising consumer price sensitivity on green products could greatly contribute to making environmental-friendly consumption more mainstream in retail markets. The main mechanism is that making some green consumers more price-sensitive will constrain retailers to revise their margins on green products downwards, which in turn will increase sustainable consumption in general.

I obtain this finding by simulating a wide range of behavioral interventions in a structural model of the demand and supply in a retail market. I calibrate the model with consumer panel data on egg consumption in France, taking organic egg as the green good. The interventions are introduced as changes in the demand function of a small group of consumers along two dimensions, the price sensitivity and the willingness to pay for organic eggs. I also prove in a simplified theoretical model that the change in price - the main mechanism considered in the model - is always important to account for when the group of affected consumers is small.

One implication of this article is that lab and field experiments evaluating the potential of a specific behavioral intervention should anticipate its effect on affected consumers' attitude towards prices. Neglecting this aspect might lead to large prediction errors when the policy is implemented at scale. Overall, my results show that retailer price response matters and call for a more systematic investigation of the price-dependency in the purchasing behavior that such interventions induce.

The main policy conclusion is that it is often better not to blindly raise consumer willingness to pay for green attributes. Instead, one might prefer to convey a sense of what a reasonable price for green product might be. Additional evaluation of past policies raising consumer price sensitivity would be interesting in order to put in perspective the results of the simulations.

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A Formal statements, proofs and extensions of the theoretical results

Proof of Lemma 1

Lemma 1. *Whatever D_2^A, the market price p_2 is higher than p^{A^*} and the demand cannot exceed $D^N(p^{A^*}) + \varepsilon$*

$$p_2 \geq p^{A^*} \text{ and } D_2^A(p_2) \leq \varepsilon + D^N(p^A)$$

Let me prove that the cut-off demand function with threshold price p^{A^*} is optimal. I want to show that the demand $D^N(p^{A^*}) + \varepsilon$ cannot be exceeded, whatever the purchasing behavior D_2^A in the affected population. Since D^N is decreasing and D_2^A is bounded by ε, it is sufficient to show that the optimal threshold price p^{A^*} is always smaller than the final equilibrium price p_2.

$$D_2(p_2) = D^N(p_2) + D_2^A(p_2) \leq D^N(p_2) + \varepsilon \overset{?}{\leq} D^N(p^{A^*}) + \varepsilon$$

Whatever D_2^A, the option of setting the price p^N is always available to the firm and generates a profit at least equal to $\Pi^N(p^N)$ - the maximal achievable profit in the absence of affected consumers. Thus, no intervention can induce a profit lower that this level.

$$\Pi^N(p^N) \leq \Pi^N(p_2) + \Pi_2^A(p_2) \leq \Pi^N(p_2) + \varepsilon(p_2 - c)$$

From this inequality, I will show that $p^{A^*} \leq p_2$, which implies our conclusion $D_2(p^2) \leq D_2(p^{A^*})$. First, by construction of p^{A^*}, we have another expression for the leftmost term $\Pi^N(p^N)$ in the previous inequality

$$\Pi^N(p^{A^*}) + \varepsilon(p^{A^*} - c) \leq \Pi^N(p_2) + \varepsilon(p_2 - c)$$

Second, notice that the function $x \longmapsto \Pi^N(x) + \varepsilon(x - c)$ is increasing on $[c, p^N]$ since Π^N is single-peaked in p^N. This concludes the proof in the case where $p_2 \leq p^N$. In the remaining case, $p^N \leq p_2$, hence $p^{A^*} \leq p_2$. We have proved Lemma 1.

Proof of Proposition 4

One can generalize some of the results to the case of a multi-product firm. This is interesting, for instance, to anticipate the effect of an intervention targeting a green product on the price of a closely-related brown product.

Let bold letters denote vector objects, such as prices $\mathbf{p}$ and demands $\mathbf{D}$, where each dimension corresponds to one of the K product sold by the monopolist. Then, Proposition 3 can be generalized in this setting.

Proposition 4 (Multi-product price effect of a marginal intervention)**.**

$$\blacksquare\mathbf{p} \underset{\varepsilon\to 0}{\sim} (\mathbf{Hess}\,\Pi(\mathbf{p}_1))^{-1}\left(\nabla\Pi_1^A(\mathbf{p}_1) - \nabla\Pi_2^A(\mathbf{p}_1)\right)$$

Since Proposition 4 implies Proposition 3 (case of one product), I will prove only the former. Assume that Π^N, Π_1^A and Π_2^A are $\mathscr{C}^2$. Assume further that Π^N has a unique maximum p^*, that Hess $\Pi^N(p^*)$ is definite negative and $\nabla\Pi_2^A(\mathbf{p}^*) \neq \nabla\Pi_1^A(\mathbf{p}^*)$. I want to prove that

$$\Delta p \underset{\varepsilon\to 0}{\sim} \left(\text{Hess}\,\Pi^N(\mathbf{p}^*)\right)^{-1}\left(\nabla\Pi_2^A(\mathbf{p}^*) - \nabla\Pi_1^A(\mathbf{p}^*)\right)$$

We can write the first-order conditions that translate the facts that the firm sets (1) $\mathbf{p_1}$ in order to maximize $\Pi_1(\mathbf{p_1})$ before the intervention and (2) $\mathbf{p_2}$ in order to maximize $\Pi_2(\mathbf{p_2})$ after the intervention.

$$\begin{cases} \nabla\Pi_1(\mathbf{p_1}) = \nabla\Pi^N(\mathbf{p_1}) + \nabla\Pi_1^A(\mathbf{p_1}) = \nabla\Pi^N(\mathbf{p_1}) + \nabla\underline{\Pi}_1^A(\mathbf{p_2}) \times \varepsilon = 0 \quad (1) \\ \nabla\Pi_2(\mathbf{p_2}) = \nabla\Pi^N(\mathbf{p_2}) + \nabla\Pi_2^A(\mathbf{p_2}) = \nabla\Pi^N(\mathbf{p_2}) + \nabla\underline{\Pi}_2^A(\mathbf{p_2}) \times \varepsilon = 0 \quad (2) \end{cases}$$

Notice that in both cases, when $\varepsilon = 0$, the program of the firm consists in setting $\mathbf{p}$ in order to maximize $\Pi^N(\mathbf{p})$. It has been previously assumed that this problem had a unique solution $\mathbf{p}^*$. Thus, one can see these two program as mere perturbations parameterized by ε of this optimization problem. Since the profit functions Π_1 and Π_2 are $\mathscr{C}^1$ with respect to ε and Hess $\Pi^N(\mathbf{p})$ is definite negative, then for ε small enough equation (1) (resp. (2)) has locally a unique solution $\mathbf{p_1}$ (resp. $\mathbf{p_2}$). When ε goes to zero, both $\mathbf{p_1}$ and $\mathbf{p_2}$ tend to $\mathbf{p}^*$.

Since Π^N is assumed to be $\mathscr{C}^2$, then $\nabla\Pi^N$ is $\mathscr{C}^1$ and we can write its first-order Taylor expansion

$$\begin{cases} \nabla\Pi^N(\mathbf{p_1}) \underset{\varepsilon\to 0}{=} \nabla\Pi^N(\mathbf{p}^*) + \text{Hess } \Pi^N(\mathbf{p}^*)\ (\mathbf{p_1} - \mathbf{p}^*) + o(1) \\ \nabla\Pi^N(\mathbf{p_2}) \underset{\varepsilon\to 0}{=} \nabla\Pi^N(\mathbf{p}^*) + \text{Hess } \Pi^N(\mathbf{p}^*)\ (\mathbf{p_2} - \mathbf{p}^*) + o(1) \end{cases}$$

We can invert Hess $\Pi^N(\mathbf{p}^*)$ as it is definitive negative. Thus, we can isolate $\mathbf{p_2} - \mathbf{p_1}$ in the previous equation and use equation (1) and (2) to conclude.

$$\begin{aligned} \mathbf{p_2} - \mathbf{p_1} &\underset{\varepsilon\to 0}{=} \text{Hess } \Pi^N(\mathbf{p}^*)^{-1} \left(\nabla\Pi^N(\mathbf{p_2}) - \nabla\Pi^N(\mathbf{p_1})\right) + o(1) \\ &\underset{\varepsilon\to 0}{=} \text{Hess } \Pi^N(\mathbf{p}^*)^{-1} \Big(\nabla\Pi_1^A(\mathbf{p_1}) - \nabla\Pi_2^A(\mathbf{p_2})\Big) + o(1) \\ &\underset{\varepsilon\to 0}{=} \text{Hess } \Pi^N(\mathbf{p}^*)^{-1} \Big(\nabla\Pi_1^A(\mathbf{p}^*) - \nabla\Pi_2^A(\mathbf{p}^*)\Big) + o(1) \end{aligned}$$

$$\text{(since } \Pi_2^A \text{ is } \mathscr{C}^1, \nabla\Pi_2^A(\mathbf{p_1}) \underset{\varepsilon\to 0}{\to} \nabla\Pi_2^A(\mathbf{p}^*) \text{ and } \nabla\Pi_2^A(\mathbf{p_2}) \underset{\varepsilon\to 0}{\to} \nabla\Pi_2^A(\mathbf{p}^*)\text{)}$$

Statement and proof of Theorem 2

Let me show that the results of section 2 can be extended to the case of symmetrical Nash-Bertrand oligopolists. I will start by introducing the notations, then state the main result - Theorem 2 - and finally prove it. Note that Theorem 2 implies Theorem 1.

Consider n symmetrical oligopolists with identical marginal cost c competing in prices. I will assume that the demand (D^N, D_1^A and D_2^A) that they face before and after the intervention are symmetrical, meaning that two firms setting the same price also face the same demand and generate the same profit. When a firm sets a price p and all the others set a price p', I will denote the demand it faces by $D(p,p')$ and the profit it generates by $\Pi(p,p') = (p-c)D(p,p')$. Partial derivatives with respect to p refer to the first argument, the firm own price.

I focus on pure symmetrical price equilibria, that is to say prices p^* such that $\Pi(p^*,p^*) = \max_{p\in\mathbb{R}} \Pi(p,p^*)$. I assume that D^N and D_1^A are smooth and that there exists before the intervention a unique symmetrical price equilibrium p_1. The fact that the size of the affected population is ε and the symmetry assumption implies that $D^A(p,p) \leq \varepsilon/n$ and $\Pi^A(p,p) \leq (p-c)\varepsilon/n$ for every price p.

Theorem 2 provides a lower bound for potential equilibrium prices following an intervention and shows that this optimum can be reached by inducing a specific purchasing behavior. I define the cut-off demand with threshold price p^A as

$$D^A(p,p') = \frac{1_{(-\infty,p^A]}(p)}{1+(n-1)1_{(-\infty,p^A]}(p')} \times \varepsilon$$

This is a mere generalization of the one-dimensional cut-off function, in which the demand is split equally between all firms below the threshold price. Since we focus on the analysis of pure symmetrical equilibria, specifying $D(p,p')$ is sufficient - there is no need to define this function for every price vector $\mathbf{p}$.

I assume that for all $p' \in \mathbb{R}^+$, $p \mapsto \Pi^N(p,p')$ is single-peaked and I refer to the peak as $p^N(p')$. The second-order optimality condition entails that $\frac{\partial^2 \Pi^N}{\partial p^2}(p,p')$ must be non-positive, and I further assume that this quantity is negative for all p', so that $p^N(p')$ is continuous is p'. Finally, I assume that the following equation - which will be motivated later - has at most one solution p^{A^*} :

$$\Pi^N(p^N(p^{A^*}),p^{A^*}) = \Pi^N(p^{A^*},p^{A^*}) + (p^{A^*}-c)\times \varepsilon/n \quad (*)$$

There is no need to assume the existence of a solution to this equation, as this can easily be shown using the intermediate value theorem - noting that for $p^{A^*} = c$ the left-hand side of the equation is non-negative and the right-hand side null, while for $p^{A^*} = p^N$ the right-hand side is larger than the left-hand side. We are now able to state theorem 2.

Theorem 2. *For all symmetrical purchasing behavior D_2^A such that there exists a pure symmetrical price equilibrium p_2, then $p_2 \geq p^{A^*}$ and $D_2(p_2) \leq D^N(p^{A^*}) + \varepsilon$.*

Moreover, if D_2^A is a cut-off demand with threshold price p^{A^*}, then p^{A^*} is a pure symmetrical price equilibrium and $D_2(p_2) = D^N(p^A) + \varepsilon$

I will start the proof by studying the case of the cut-off demand, and then prove that it is impossible to do better. Let me show that the price p^{A^*} introduced previously is indeed a symmetrical equilibrium price when D_2^A is a cut-off demand with threshold price p^{A^*}. When a firm faces a cut-off demand with threshold p^{A^*} from the affected population, the firm either sets the price p^{A^*}, or sets a price that is optimal when ignoring the affected population. In the first case, it generates a profit

$$\Pi^N(p^{A^*},p^{A^*})+\Pi_2^A(p^{A^*},p^{A^*})=\Pi^N(p^{A^*},p^{A^*})+\frac{\varepsilon}{n}(p^{A^*}-c)$$

In the second case, it sets a price p that maximizes $\Pi^N(p,p^{A^*})$, which by definition must be $p^N(p^{A^*})$. Therefore, the firm generates in the second case a profit

$$\Pi^N(p^N(p^{A^*}),p^{A^*})$$

By equation (*) that defines p^{A^*}, the firm has no interest to deviate from p^{A^*} to p^N as both generate the same profit. Therefore, p^{A^*} is indeed a pure symmetrical price equilibrium and the corresponding demand is $D^N(p^A)+\varepsilon$.

What remains to be shown is that these price and demand cannot be improved. Consider any symmetrical purchasing behavior D_2^A such that there exists a symmetrical equilibrium price p_2. Since no firm has any interest to deviate from p_2,

$$\Pi^N(p_2,p_2)+\Pi^A(p_2,p_2)\geq\Pi^N(p^N(p_2),p_2)+\Pi^A(p^N(p_2),p_2)$$

I will show that the same price equilibrium can be obtained with a cut-off demand with threshold price p_2. As previously, it is sufficient to show that no firm has an interest to deviate to $p^N(p_2)$, that is to say

$$\Pi^N(p_2,p_2)+\frac{\varepsilon}{n}(p_2-c)\geq\Pi^N(p^N(p_2),p_2)$$

This comes directly by combining the previous inequality, the fact that $\frac{\varepsilon}{n}(p_2-c)\geq\Pi^A(p_2,p_2)$ and that $\Pi^A(p^N(p_2),p_2)\geq 0$. Thus, the same price could have been obtained under a cut-off demand with threshold price p_2 in the affected population. Moreover, the equilibrium demand cannot be smaller with the cut-off demand than with D_2^A since

$$D_2^N(p_2,p_2)+\varepsilon\geq D_2^N(p_2,p_2)+D_2^A(p_2,p_2)$$

It is now sufficient to compare cut-off demand functions with one another and find the lowest threshold price for which there exists a symmetrical equilibrium. Define T as the set of prices p such that p is a symmetrical equilibrium in presence of a cut-off demand function with threshold price p. Using the no-deviation condition found earlier, we have

$$T = \{p \in \mathbb{R}_+ \mid \Pi^N(p,p) + \frac{\varepsilon}{n}(p-c) \geq \Pi^N(p^N(p),p)\}$$

By continuity of Π^N and p^N, T is a closed set, and since it has bounded from below $\inf T \in T$. Moreover, for the same reason, $\inf T$ satisfies the equation

$$\Pi^N(\inf T, \inf T) + \frac{\varepsilon}{n}(\inf T - c) \geq \Pi^N(p^N(\inf T), \inf T)$$

By uniqueness of p^{A^*}, it must be that $\inf T = p^{A^*}$. In particular, for all $p \in T$, $p^{A^*} \leq p$ hence the final demand at the equilibrium p^{A^*} is higher than that at the equilibrium p. This concludes the proof.

Let me summarize quickly the rationale. For any purchasing behavior D_2^A that leads to a symmetrical equilibrium price p_2, then the cut-off demand with threshold p_2 leads also to a symmetrical equilibrium price p_2 and the corresponding equilibrium demand is no lower than with D_2^A. Then, it suffices to ask what threshold price p^A generates the lowest price - hence, the highest demand. It has been shown that $p^A = p^{A^*}$ is the best possibility.

B Likelihood and price sensitivities in a random logit model

Let me start by providing formulas valid at the individual level, where α_i can be considered as a given constant. Denoting $\widetilde{U}_{ijt}$ the product-specific non-stochastic term in equation 2 - that can be directly computed from data and parameter values.

$$\widetilde{U}_{ijt} = \alpha_i \times p_{jt} + \beta \cdot \mathbf{x}_j + \gamma \times v_{ijt} \tag{8}$$

Since $\widetilde{U}_{ijt} = U_{ijt} + u_{ijt}$ and the stochastic noise terms u_{ijt} are independent and follow a Gumbel distribution, then the probability s_j that product $j \in J_{it}$ yields that highest utility as a function of the $\widetilde{U}_{ijt}$ writes

$$s_{ijt} \underset{\text{déf}}{=} P\left(U_{ijt} = \max_{k \in J_{it}} U_{ikt}\right) = \frac{\exp(\widetilde{U}_{ijt})}{\sum_k \exp(\widetilde{U}_{ikt})} \tag{9}$$

The derivative of s_j with respect to the price p_{kt} of product $k \in J_{it}$ has a simple expression, that will later be used in computing the Ω matrix.

$$\frac{\partial s_{ijt}}{\partial p_{kt}} = (\delta_i^j - s_{ijt}) s_{ikt} \tag{10}$$

The likelihood of the purchase choices at the household level, assuming α is known and product $j(i,t) \in J_{it}$ has been chosen by household i at period t

$$L = \prod_{i \in I} \int_{\mathbb{R}^+} \left(\prod_t \frac{\exp(\widetilde{U}_{ij(i,t)t})}{\sum_k \exp(\widetilde{U}_{ikt})} \right) f(\alpha_i \mid \theta_{LN})\, d\alpha \tag{11}$$

Estimating the demand model consists in finding the values for the parameters β, γ and θ_{LN} that maximize this llikelihood. Numerically, we make use of the *apollo_estimate* function from the R *apollo* library. This function approximates the integral by a quasi Monte Carlo method, using 200 Halton points. More information are available in section 4.6 of the library user manual Hess and Palma [2019].

C Bayesian posterior expectations at the household level

Estimating a multinomial logit model with random coefficient yields population-wide parameters estimates θ_{LN} for the price sensitivity α_i. Denoting $f(\alpha \mid \theta_{\mathrm{LN}})$ the corresponding density, Bayes rule gives the density $g(\alpha \mid \theta_{\mathrm{LN}}\ , \ \mathrm{achats}_i)$ of the posterior distribution of the α coefficient conditionally on the estimated parameters θ_α of the population-wide distribution and the purchase choices achats_i made by household i.

$$g(\alpha \mid \theta_{\mathrm{LN}}\ , \ \mathrm{achats}_i) = \frac{L(\mathrm{achats}_i \mid \alpha)\ f(\alpha \mid \theta_{\mathrm{LN}})}{\int_{\mathbb{R}^+} L(\mathrm{achats}_i \mid \alpha')\ f(\alpha' \mid \theta_{\mathrm{LN}})\ d\alpha'} \tag{12}$$

The coefficient $\alpha_i^{\mathrm{BAYES}}$ is then defined as the expectation of this conditional distribution $g(\alpha \mid \theta_{\mathrm{LN}}\ , \ \mathrm{achats}_i)$

$$\alpha_i^{\mathrm{BAYES}} = \frac{\int_{\mathbb{R}^+} \alpha\ L(\mathrm{achats}_i \mid \alpha)\ f(\alpha \mid \theta_{\mathrm{LN}})\ d\alpha}{\int_{\mathbb{R}^+} L(\mathrm{achats}_i \mid \alpha')\ f(\alpha' \mid \theta_{\mathrm{LN}})\ d\alpha'} \tag{13}$$

As for the likelihood function, these integrals are numerically approximated by quasi Monte Carlo using 200 Halton points, using the function *conditionals* from the *apollo* library. More information is available in section 9.14.1 from the *apollo* library manual Hess and Palma [2019].

D Equilibrium search algorithm

Starting from $\mathbf{u_0} = \mathbf{p_1}$ the equilibrium price before the intervention, the algorithm iterates the rule

$$\mathbf{u_{k+1}} \longleftarrow \frac{1}{1-\tau}\left[\mathbf{c} - \blacksquare(\mathbf{u_k})^{-1}\mathbf{D}(\mathbf{u_k})\right]$$

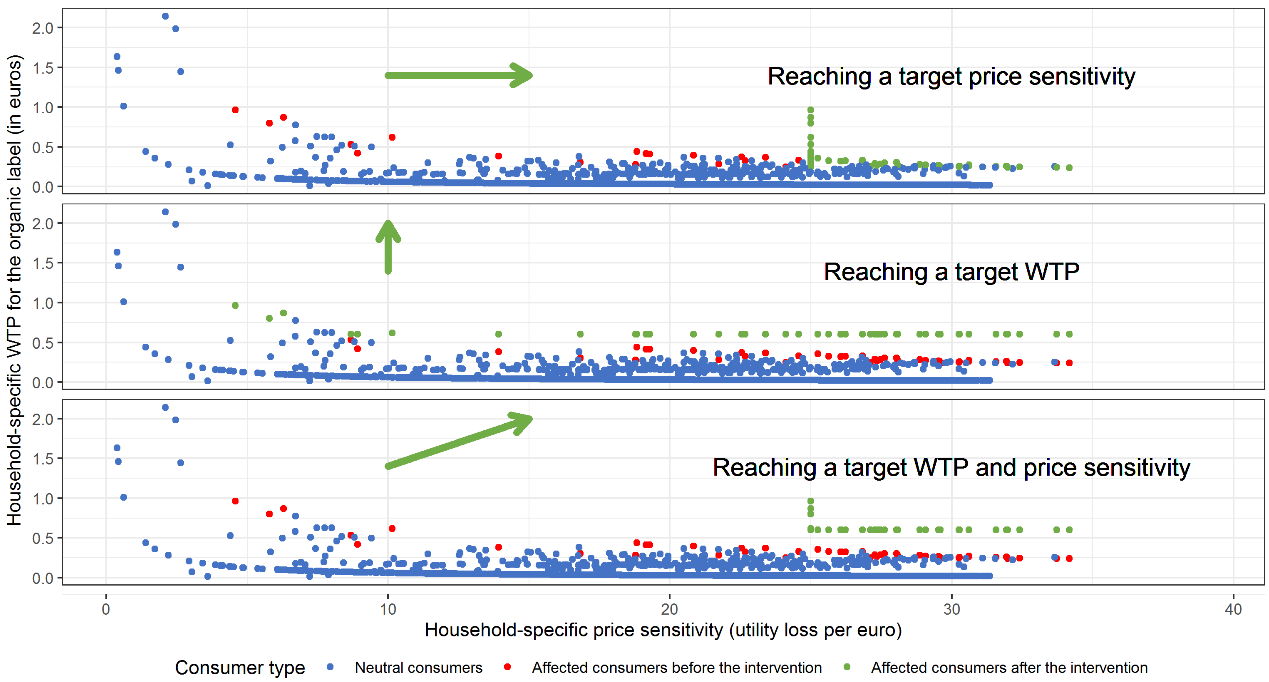
By continuity, if the sequence converges to $u_\infty \in \mathbb{R}^K$, then the first-order condition is satisfied by u_∞

$$\blacksquare(\mathbf{u}_\infty)\left[(1-\tau)\mathbf{u}_\infty - \mathbf{c}\right] + \mathbf{D}(\mathbf{u}_\infty) = 0$$

In practice, the algorithm is stopped once the step of an iteration $\|\mathbf{u_{k+1}} - \mathbf{u_k}\|_\infty$ is smaller than 10^{-7} euros.

Note that this algorithm is based on a first-order condition, which is necessary but not sufficient for optimality. Therefore, when the profit function of a firm has several local maxima, the iteration can get stuck in one of them and may not lead to a profit-maximizing price. As I consider only small changes in the demand function and do not explore the domain of very high value for the price sensitivity, it is unlikely that such numerical issue arise.

E Illustration of the transformations



Notes: The figure illustrate the effect of the simulated interventions on the position of the households in the (price sensitivity, willingness to pay) plane. The position of the affected households before the intervention is in red and the one after the intervention is in green. The other households, in blue, are unchanged.

Figure 7: How interventions change the demand of affected households in the simulations