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Testing Dynamic Behavior**

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# Do consumers correctly expect price reductions? Testing dynamic behavior\*

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## Abstract

The assumption that consumers are fully rational and hold correct expectations over prices is demanding in dynamic settings. We claim that it is testable provided that market-level data on prices and purchases are available. We find that consumers hold simple expectations on the timing of promotions for music albums: everything happens as if consumers were aware of reductions but did not revise their beliefs over time. The anticipation effect, due to strategic delaying of purchase, amounts to 17% of the decision of purchase during regular periods. These results have implications in terms of demand estimation, optimal pricing and welfare computations.

**Keywords:** Testing expectations; dynamic behavior; sales; demand models; bounded rationality.

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# 1 Introduction

The importance of taking agents' dynamic behavior into account has been well emphasized by the theoretical literature in industrial organization. Consumers are often assumed to anticipate future prices and to behave strategically. For instance, [Stokey \(1981\)](#) requires consumers to be perfectly forward-looking in order to construct the unique perfect equilibrium that implements the Coasian outcome. A vast empirical literature has been devoted to the estimation of games in which agents are fully rational and dynamic: seminal contributions include [Aguirregabiria and Mira \(2007\)](#), [Bajari, Benkard, and Levin \(2007\)](#), [Pesendorfer and Schmidt-Dengler \(2008\)](#). Intertemporal models of demand that were developed for example in [Nair \(2007\)](#) or [Esteban and Shum \(2007\)](#) rely on the assumption that agents are perfectly forward-looking, which involves complex dynamic programs. Though many papers take full rationality for granted, the latter assumption is rather demanding in a dynamic setting since it requires agents to hold correct expectations over the future state of the world.

Structural dynamic models of demand like those in [Hendel and Nevo \(2006a\)](#) and [Gowrisankaran and Rysman \(2012\)](#) assume that consumers are fully rational but that firms fix prices according to some Markov process. Under this simplifying assumption, the estimated demand is similar to the one that would be estimated under a different assumption, namely: "firms fix prices optimally, consumers expect a Markov process". However, the derivation of optimal prices and welfare computations would be different. A game in which both firms and consumers behave optimally differs from a game in which fully rational firms face non fully rational consumers; outcomes including equilibrium prices, purchases and profits are not the same. To simplify the estimation, [Ching and Ishihara \(2012\)](#) depart explicitly from the fully rational expectation assumption. [Hendel and Nevo \(2013\)](#) consider several hypotheses about consumers' expectations, perfect foresight as opposed to rational expectations, and estimate a model of demand under different assumptions.

In the specific context of promotions, theoretical papers have already invoked bounded rationality to lighten to the assumption of correct anticipations. [Villas-Boas and Villas-Boas \(2008\)](#) derive the optimal duration between sales as well as the optimal length of a sale in a setting where informed consumers forget their preferences, while uninformed consumers are willing to experiment new products. [Heidhues and Kőszegi \(2014\)](#) assume that consumers have rational expectations about sales but are loss adverse in the spirit of [Kahneman and Tversky \(1979\)](#). They show that a monopolist's optimal price distribution consists of low, variable "sale" prices on the one hand, and of high, atomic "regular" prices on the other hand, consistently with what is observed in many retail markets.

To understand better how consumers form their expectations about the price process, we need either to ask them directly what they know about prices, or to observe how the aggregated demand reacts to price changes. The first possi-

bility requires individual data, provided that surveys are available on that topic. However, most of the time econometricians dispose of market-level data only.

This paper argues that the nature of consumers' expectations is testable from market-level data.<sup>1</sup> A simple method is proposed to determine whether consumers hold correct beliefs over the price process. We exploit price variations and their corresponding responses in terms of purchases to infer the nature of consumer behavior in a dynamic setting. We show that perfect foresight, myopia or expectations based on a time-independent information set correspond to distinct patterns of demand, which yields testable predictions.

From market-level data of prices and purchases of albums, we document first several empirical facts regarding promotions and consumer behavior. The price process is composed of a regular price followed by occasional price reductions: sales or durable price changes. Price stickiness makes a repeated static game *à la* Varian (1980) less likely than intertemporal price discrimination motives. As in Pesendorfer (2002), the probability of a price reduction increases as time goes by, which shows that the timing of promotions is not random and that price reductions can be roughly predicted. We observe then a peak of demand at the beginning of promotions; this peak is higher when the time elapsed since last promotion increases, which indicates that there is accumulation of consumers in the market. Interestingly, during a period with a regular price the pattern of demand is not decreasing, but flat. If consumers expect prices correctly and delay their purchases accordingly, the demand must decrease *ceteris paribus* since the gain from waiting increases. Even if *some* (loyal) customers had perfect foresight, a decreasing pattern should still be observed. By contrast, a flat pattern indicates somehow that consumers do not update correctly their beliefs.

Second, we present a stylized theoretical model that relates the nature of consumer anticipations about prices to demand in a durable-good setting. Facing firms that hold occasional promotions, consumers who cumulate in the market are responsible for a decreasing pattern of purchases during sales. Consumers with correct expectations should anticipate that a sale is more and more likely to occur as time goes by. On the contrary, myopic consumers should be indifferent to a sale approaching. Consumers with time-independent anticipations differ from the latter since they care about the price gap between the regular and the discounted price. The observed pattern of purchases is consistent with the accumulation of low-valuation consumers waiting for discounts, but is not consistent with the presence of at least some consumers endowed with correct foresight. The model provides further tests to discriminate among two remaining *scenarii*: myopic consumers *versus* consumers with static, time-independent beliefs.

Third, we implement these tests on the data. Empirical evidence suggests

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<sup>1</sup>Markets with highly volatile prices are not adequate since it would be hard to disentangle the price effect from the anticipation effect (see *infra*). Markets with sticky prices and occasional price changes (including promotions) are more appropriate.

that consumers are aware of promotions and wait for them, but that they have a wrong timing in mind –or that they form “simple” expectations which they do not update accordingly as time goes by. Indeed, the demand at the regular price is higher when the difference between the regular price and the discounted price increases. It is also decreasing with the ratio between that “price gap” and the time separating promotions, as if consumers delayed strategically their purchases based on time-independent beliefs. Introducing next both randomness and heterogeneity in the previous model, we estimate demand thanks to a fixed-effect Poisson model which permits to reject both perfect foresight and myopia. Finally, we find that the decision of purchase results from an intertemporal trade-off that depends at 83% on the current price (“price effect”) and at 17% on the expected gain from waiting a lower price, which we call the “anticipation effect”. This behavior turns out to be consistent with time-dependent beliefs.

The literature in empirical IO has already argued that consumers may not be perfectly forward-looking. [Ching, Erdem, and Keane \(2009\)](#) bring evidence that consumers may not consider a product every period. [Clerides and Courty \(2010\)](#) also document consumer inattention by looking at specific sales resulting in quantity surcharges. [Seiler \(2013\)](#) explains that it may be difficult for consumers to form rational expectations about prices because they may not know when the last sale happened. In our example, consumers behave as if they did not revise their beliefs over time, hence as if they were expecting a Markov price process. Indeed, the *scenario* that fits best observed consumer behavior is the case where consumers expect a price reduction with some constant probability over time:  $\mathbb{E}(p_{t+1}|p_t) = (1 - \lambda)p_t + \lambda \underline{p}$ , where  $\lambda$  stands for the probability of a promotion and  $\underline{p}$  is the discounted price. This AR(1) assumption is often made in the literature devoted to the structural estimation of dynamic discrete-choice models or DDCM ([Hendel and Nevo, 2006a](#); [Gowrisankaran and Rysman, 2012](#)). Again we show how such an assumption can be tested, and how we accept this hypothesis in our data.

Within the estimation of structural dynamic models of demand, departing from the assumption of perfect foresight has an impact on the computation of optimal pricing. This paper provides therefore also some insight to the supply side since a better knowledge of consumer behavior affects directly firms’ strategies. These results may help explaining why actual pricing consists in holding occasional sales. From [Conlisk, Gerstner, and Sobel \(1984\)](#) we know that in a durable-good setting, firms facing consumers with perfect foresight and who accumulate in the market should charge equilibrium price cycles in which the price decreases. When consumers hold time-independent beliefs, one expects firms to decrease their prices periodically. The presence of menu or switching costs sounds like another possibility to explain why firms do not use the whole spectrum of prices. Finally, these results have also significant implications on welfare analyses.

The paper is organized as follows. Section 2 presents the data we use. Section 3 documents empirical facts about prices and demand patterns before, during and after price reductions. In Section 4, a stylized model explains how the demand is

formed from expectations according to different *scenarii* on consumers’ behavior, and derives some testable predictions. Section 5 is devoted to the estimation of a model of demand that enables us to test previous predictions, to discriminate among the different *scenarii* and to measure the anticipation effect. Section 6 discusses our results and Section 7 concludes.

## 2 Data

We exploit data from the largest French music retailer, selling about 25% of albums. The music industry is heavily concentrated in France: both non-specialized and specialized stores have respective aggregated market shares of 40%. Independents and other retailers share the remaining 20%. Our working sample is made up of the 121 most popular records sold in our retailer’s 10 main stores from January 2003 to November 2006. Six stores are located in Paris while the four last stores are in other large French cities: Grenoble, Lille, Lyon and Toulouse. Our balanced panel has 245,021 observations after the elimination of three small album-stores with few sales. An observation corresponds to some album  $j$  that was sold (or not) by store  $r$  in week  $t$ ,  $t \in \llbracket 1 ; 203 \rrbracket$ . For each album we know the band, the song, the name of the record label (Sony, Warner, EMI, etc.), how many albums were sold in each store, *i.e.*, the quantity  $q_{jrt}$ , and how much revenue  $R_{jrt}$  these sales generated. Prices are computed from the ratio  $\frac{R_{jrt}}{q_{jrt}}$ . When  $q_{jrt} = 0$ , *i.e.*, when no CD was sold, the price is missing.

Observations with no purchase account for 48% of the sample. To recover missing prices, we follow a standard procedure described by the Kilts Center for Marketing (Chicago Booth GSB) that provides publicly databases including data on ketchup like the one used by [Pesendorfer \(2002\)](#). We rely mainly on adjacent prices; we also use the fact that there is a national pricing policy. The complete procedure is described in [Appendix A](#).

These albums come from the “world- and pop- music department”. All of them were released before 2001, which rules out new albums with specific price patterns. Since CDs do not depreciate physically over time, and because consumers generally purchase an album at most once, these products are viewed as durable goods. Most famous albums in our sample include *Nevermind* (Nirvana), *Platinum Collection* (Queen), *One* (The Beatles), *Andy Warhol* (The Velvet Underground), *Wall* (Pink Floyd), etc. The whole list of albums is provided in [Appendix B](#). Interestingly, this selection seems less exposed to freshness depreciation in the sense of [Ching and Ishihara \(2012\)](#).

[Figure 1](#) displays typical joint patterns of purchases and prices at the album-store level (and at weekly frequency). Price patterns exhibit long periods with a high price (the regular price) and occasional price cuts (price reductions) followed by a return to the regular price.

## 2.1 Price reductions: sales and durable price changes

We define a “price reduction” as a downward change of a “price level”. Price levels correspond to most frequent prices at the album-store level (see Appendix A) after inflation has been taken into account, as shown in Figure 1. Each album-store has between 1 and 10 price levels. The regular price – the highest price level – is charged more than 60% of the time (Table 1, Column 2), which confirms that prices are sticky in this market. Moreover, 95% of the time, the price charged belongs to the four highest prices.<sup>2</sup>

As a striking feature, the firm uses the same price for many different albums. The most frequent price concerns about 12% of our 121 albums while three (resp. five) prices are used for 1/3 (resp. almost 1/2) of albums. This empirical evidence is consistent with menu costs, or switching costs that make it costly for the firm to change prices frequently.

In the rest of the paper, we focus on sequences of high prices followed by – potentially multiple – price reductions. Such sequences are defined by the moment when the price decreases. Moreover, we restrict our attention to sequences whose high price is the regular price. If several price reductions occur consecutively, we consider only the first one. We also exclude sequences for which the beginning or the end is not available in the data. This selection yields 2,833 “high-price/low-price” sequences that typically last 40 weeks: 30 weeks with the regular price and 10 weeks with a discounted price, as shown by Table 2.

We get rid of specific price reductions which last either one or two weeks, and which correspond to discounts offered to regular shoppers owning a loyalty card. These targeted promotions are part of the firm’s customer-oriented price policy. There are 2,314 such price reductions with a median discount of 9.3%. Since they are not the object of our interest here, we do as if there was no price cut during those weeks.

As made clear by Figure 1, one has to make the distinction among the remaining price reductions that can be of two sorts: either sales or durable price changes.

On the one hand, sales are occasional and last five weeks on average, with a discount of about 38% (Table 3, top panel). The average price on (off) sale is 9.9 (16.2) euros. Every album-store is observed on sale about once a year. There is no clear seasonality in the timing of promotions. On average, every week in a store 7.5% of albums are on sale.

On the other hand, durable price changes correspond to a new, lower regular price. For instance, the regular price of *Greatest hits* (Janis Joplin) falls from 11.5 to 10.6 euros on August 2005. We call this switch a “durable price change”

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<sup>2</sup>Price levels are less likely to vary according to idiosyncratic shocks of demand: otherwise, the distribution of these price levels would not look like the one displayed by Table 1.

(Table 3, bottom panel). Such changes last longer than sales do (about 22 weeks<sup>3</sup>) but imply a discount close to 35%. Moreover, almost every album experiences at least one durable price change during our period of observation, which is consistent with a tougher price competition with Internet and the development of peer-to-peer devices.

## 2.2 Purchases

As documented by the literature devoted to promotions, and as shown by Figure 1, the demand sounds much responsive to promotions. 7.1 units per week on average are sold during price reductions, against 1.1 unit otherwise: the demand is thus 6.8 times higher during a promotion. Figure 2 represents the average pattern of purchases between twelve weeks before (T-12) and nine weeks after (T+9) the beginning of a promotion. There is a clear peak of purchases which amounts to almost 10 times the usual demand. Since we aggregate daily data at the weekly level, the first week of a price reduction mixes necessarily some days with a high price and some days with a low price: the average quantity sold sounds therefore smaller in the first week than in the second week of a promotion. However it is expected that the true value of the first week exceeds the peak observed here at the second week. Consistently with Figure 1, promotions are characterized by a peak followed by some strongly decreasing pattern of demand. It suggests that consumers have been cumulating before the promotion, *i.e.*, that they have stayed in the market because they are still interested in buying the album, but at a lower price.<sup>4</sup>

More surprisingly, we observe hardly any decreasing pattern of demand during weeks with a regular price. The average quantity sold amounts to 1.3 one month after a promotion and to 1.1 one month before. It is equal to 1.2 two months after and to 1.0 two months before. On the whole, previous differences are not significant at usual levels. The pattern of purchases seems roughly flat during regular periods. If consumers had correct expectations about prices and the timing of price reductions, one would expect demand to fall as the beginning of the price reduction approaches: delaying purchase is then more profitable since the opportunity cost of waiting for a promotion is lower.<sup>5</sup>

## 3 Empirical facts on prices and purchases

In this section, we document several facts about sales to validate previous observations *ceteris paribus*. First, from the observation of prices only, we invoke the

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<sup>3</sup>By construction, durable price changes that are not observed being followed by any promotion are ruled out, hence it is a lower bound.

<sup>4</sup>See Section 4 for a more formal argument.

<sup>5</sup>See Section 4 for a more formal argument.



stickiness to reject a price-setting model *à la* [Varian \(1980\)](#). Moreover, we show that price reductions are not deterministic but predictable. Besides, using both prices and purchases, we document the existence of a peak of purchases at the beginning of promotions and the flatness of demand at the regular price. Together these facts suggest that there is accumulation of consumers in this durable-good market, *i.e.*, consumers stay in the market as potential buyers, waiting for lower prices; and that consumers do not hold correct expectations about prices.

### 3.1 Prices

Firms spend money and time to analyze consumer behavior in their marketing departments. For this reason, it is more likely that they behave optimally. We argue here that the present firm does not set prices naively and that her behavior turns out to be consistent with what an optimal firm would do.

First, [Figure 1](#) shows that prices are sticky, which contradicts the idea that the firm plays a repeated static strategy like in [Varian \(1980\)](#) (see also [Berck, Brown, Perloff, and Villas-Boas, 2008](#)).

Following [Pesendorfer \(2002\)](#), we estimate secondly the impact of the duration since the last promotion on the probability of having a price reduction.<sup>6</sup> We define  $S_{jrt}$  as a variable equal to 0 when the price is high, and to 1 during the first period of a price reduction. All periods following the first week of promotions are disregarded in this analysis. We specify a Logit model with fixed effects:

$$S_{jrt} = \mathbb{1}[\beta_{dur} \text{duration}_{jrt} + \gamma t + \xi_{jr} + \epsilon_{jrt} > 0]. \quad (1)$$

[Chamberlain \(2010\)](#) showed that the parametric assumption for the distribution of the error term  $\epsilon_{jrt}$  is necessary: the identification of the parameters of interest  $\theta = (\beta_{dur}, \gamma)$  fails as long as this distribution is not logistic. It is indeed sufficient: using a semiparametric estimation technique, namely the conditional likelihood approach *à la* [Rasch \(1960\)](#), [Andersen \(1973\)](#), [Chamberlain \(1984\)](#) and [Magnac \(2004\)](#), it is possible to identify and estimate  $\theta$ . Results are displayed by [Table 4](#), Column 1. We reject  $H_0 : \beta_{dur} = 0$  against  $H_a : \beta_{dur} > 0$  at 5%, which indicates that the probability of a promotion is increasing with the duration<sup>7</sup> since the last price reduction. Allowing  $\beta_{dur}$  to vary over time (Column 2), we check that the relationship is still increasing. Put differently, a price reduction is more likely as time goes by, and can therefore be predicted by consumers who update their beliefs accordingly. Promotions are thus not deterministic, but predictable.

In the same vein, the length of a promotion increases with the duration since the last price reduction, which is a firm's best response to consumer accumulation. The larger the interval between sales, the longer it takes to empty out a bigger

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<sup>6</sup>There is no particular seasonality in the timing of promotions, contrary to what happens in the clothing sector for instance.

<sup>7</sup>The covariate *duration* will also be denoted *after* in what follows (see *infra*).

stock of awaiting consumers: such a correlation is obtained in Table 4, Columns 3 and 4. Therefore, this analysis does not rule out the possibility that the present firm behaves as if she were fully rational and dynamic.

### 3.2 Purchases

**Fact 1: a peak of demand occurs at the beginning of price reductions, followed by a decreasing pattern of purchases.**

When there is a price reduction, we define the variable *during* as the elapsed time since the beginning of that price reduction. *During* is equal to 1 the first week of the promotion, 2 the second week, etc. We recover the net pattern of purchases during price reductions after controlling for album-store and week effects:

$$q_{jrt} = \beta_d \text{during}_{jrt} + \beta_x X_{jrt} + \xi_{jr} + \delta_t + \epsilon_{jrt}. \quad (2)$$

Further controls  $X_{jrt}$  include the number of albums on sale in store  $r$  at time  $t$ , as well as the number of albums on sale by the same author, which both account for the substitution effect across promoted products widely documented in [Hosken and Reiffen \(2004\)](#). *De facto*, we find some substitution between those products and there is also evidence of bundle effects for albums by the same author. The current (discounted) price  $\underline{p}_{jrt}$  could have been introduced as a control variable: this price is likely to be correlated with  $\xi_{jr}$  but less with the idiosyncratic shock  $\epsilon_{jrt}$ . Including this price as a covariate does not change the estimates of the pattern which are also robust to controlling for album and store-week effects instead of album-store and week effects.

Figure 3 depicts the whole pattern of purchases during either a price reduction or a sale. It is highly decreasing and the demand falls continuously after the second week.<sup>8</sup> The magnitude of the effect at stake is large: *ceteris paribus* there are four more albums sold on the second week than on the tenth week of a price reduction. Furthermore, a small increase after the 11<sup>th</sup> week indicates a return to some stationary level. These results are consistent with previous findings by [Boizot, Robin, and Visser \(2001\)](#), [Pesendorfer \(2002\)](#) and [Hendel and Nevo \(2006b\)](#) where consumers waiting for low prices cumulate in the market.

**Fact 2: the pattern of demand at the regular price is flat.**

We now define the variable *before* during periods with a regular price as the number of remaining weeks before the price reduction. *Before* is equal to 1 the first week before a price reduction, 2 the week two weeks before, etc. To test whether the pattern of purchases is decreasing or flat in such periods, we specify:

$$q_{jrt} = \beta_b \text{before}_{jrt} + \beta_x X_{jrt} + \xi_{jr} + \delta_t + \epsilon_{jrt}. \quad (3)$$

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<sup>8</sup>Due to the aggregation of daily into weekly data.

Here, the current price  $p_{jrt} = \bar{p}_{jr}$  cannot be introduced as a covariate because its effect would not be identified in the presence of album-store fixed-effects  $\xi_{jr}$ . Indeed, the estimation is done on “high-price/low-price” sequences for which the price is equal to the highest price level.<sup>9</sup>

Figure 4 displays the net pattern of purchases during periods with a regular price. It remains still roughly flat. Excluding the first week,<sup>10</sup> the magnitude of the decreasing pattern, if any, would be less than .1 unit in 20 weeks, *i.e.*, .005 album per week.

Similarly, we define the variable *after* as the elapsed duration since the last price reduction and estimate:

$$q_{jrt} = \beta_a \text{after}_{jrt} + \beta_x X_{jrt} + \xi_{jr} + \delta_t + \epsilon_{jrt}. \quad (4)$$

Figure 5 exhibits the net pattern of purchases after a price reduction. By contrast, we find some decreasing pattern here. The corresponding magnitude is about  $-.0125$  units per week and per store, which hardly accounts for 1% of average purchases.

There is some asymmetry between what happens before and what happens after a price reduction. If consumers had perfect foresight, or at least rational expectations about the price process, decreasing patterns of demand before and after a price reduction would be expected, due to strategic delaying of purchases. Consumers may be heterogeneous in the way they form their expectations: a fraction of the population might have better anticipations about prices than others. This asymmetry can also stem from the fact that stores do not change labels right after a price reduction. Regular shoppers are perhaps also less prone to forget that a promotion had recently occurred. On the whole, the effect pointed out by Figure 5 seems too weak to suggest that consumers are forward-looking. If any, it provides empirical evidence against the idea that the pattern of demand is flat as the resulting sum of a decreasing pattern coming from an anticipation effect, and of an increasing pattern coming from a “re-stocking effect” (after a price reduction the stock of consumers has been emptied out, it may reform thereafter).

These results suggest that consumers do not expect price reductions correctly. On a US market for college textbooks, [Chevalier and Goolsbee \(2009\)](#) also wonder whether students are forward-looking or not. In this market, agents behave as if they held correct expectations. However, the test was different in nature since it relied on possibilities of resale: textbooks are frequently reedited and forward-looking consumers should update their probability of resale accordingly.

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<sup>9</sup>Precisely to abstract from the accumulation effect.

<sup>10</sup>Once again the first week before a price reduction mixes days with high and low prices: purchases on that week are therefore spuriously higher than purchases the weeks before.

## 4 Dynamic demand and consumer expectations

We explain here what can be learned about consumer expectations from the observation of demand for a durable good. We present a stylized monoproducer “toy model” to capture all the necessary intuitions and to stress the link between consumer expectations and demand in a dynamic framework.

We consider a discrete time setting. We assume that a firm alternates between a regular price  $\bar{p}$  during  $n$  periods and an occasional lower price  $\underline{p}$  during  $s$  periods called sales. Such cycles repeat over time. The demand comes from impatient consumers who discount the future at factor  $\delta \in [0; 1]$ . These consumers are heterogeneous in their valuation  $v \in [0; +\infty[$  distributed according to some cdf  $F(\cdot)$ . Their current utility at time  $t$  writes  $v - p_t$ . Every period new identical cohorts of consumers with a mass normalized to one arrive in the market. Old consumers stay in the market with probability  $\alpha \in [0; 1]$  until the next period. They exit the market, or die with probability  $1 - \alpha$ . This technical assumption ensures that the demand does not explode over time. The timing is the following. At the beginning of period  $t$ , a new cohort arrives and joins the remaining consumers. All consumers observe prices. The demand is formed. People who do not purchase either drop out, or stay in the market until period  $t + 1$  with probability  $\alpha$ .

Dynamics is at stake only if some consumers remain in the market, *i.e.*, if  $\alpha > 0$ . When  $\alpha = 0$ , one has a repeated static game in which buyers of period  $t$  are new consumers whose valuation is higher than the current price, regardless of their expectations. The demand is equal to  $1 - F(\bar{p})$  when the price is high and to  $1 - F(\underline{p})$  otherwise, which yields to flat patterns of purchases depicted in Figure 6. On the contrary, when  $\alpha > 0$ , the pattern of purchases depends on consumer expectations about prices and sales.

### 4.1 Perfect foresight, or: imperfect foresight and time-dependent information

We first suppose that consumers have perfect foresight regarding prices. They anticipate correctly the firm’s price cycles and know exactly where they are in those cycles. In period  $t \in \llbracket 1; n \rrbracket$ , a consumer with valuation  $v$  buys if and only if:

$$v - \bar{p} \geq (\alpha\delta)^{n-t+1}(v - \underline{p}), \quad (5)$$

that is, if his valuation exceeds some reservation value:

$$v \geq v_n(t) = \frac{\bar{p} - (\alpha\delta)^{n-t+1}\underline{p}}{1 - (\alpha\delta)^{n-t+1}} = \bar{p} + \frac{(\alpha\delta)^{n-t+1}}{1 - (\alpha\delta)^{n-t+1}}(\bar{p} - \underline{p}).$$

Because  $v_n(t)$  increases with time  $t$ , the demand  $1 - F(v_n(t))$  is composed only of new cohorts of consumers.  $v_n(t)$  does not really depend on  $n$  but rather on the

remaining time until the next sale  $n - t + 1$  –so does the demand. In particular, it decreases with  $t$ : as time goes by, the date of the sale is approaching, more and more consumers wait for it, which induces a declining pattern of purchases over time when the price is high. The latter analysis is the dual of the declining pattern of prices obtained in [Conlisk, Gerstner, and Sobel \(1984\)](#). In their setting, a firm facing heterogenous consumers with discrete valuations - namely two types - uses price cycles in which the price decreases. The firm wants high valuation consumers to purchase as soon as they enter the market: prices decrease to make them indifferent between purchasing immediately or later on; as a result, the firm lowers prices as a sale approaches while quantities are constant over time. Here we fix the firm’s strategy at some constant price during  $n$  periods, and purchases decrease, which reflects that consumers are more likely to wait for the sale.

More generally, a declining pattern should be observed not only if consumers perfectly foresight prices, but also if at least some consumers know that the sale is closer, or more likely, as time  $t$  goes by. Even under imperfect information, a declining pattern will arise as soon as consumers are aware at time  $t+1$ , given their information set, that they have a greater incentive to wait than at time  $t$ . We will say in that case that consumers face imperfect but time-dependent information about sales.

We now turn to the pattern of purchases during sales. At the beginning of the sale, in period  $n + 1$ , consumers of all cohorts are present in the market. At the end of every period  $t$ , consumers whose valuations were lower than  $v_n(t)$  but higher than  $\underline{p}$  decided to wait for a sale. Since they have stayed in the market until period  $n + 1$  with probability  $\alpha^{n-t+1}$ , there is a peak of demand at the beginning of the sale equal to

$$\sum_{t=1}^n \alpha^{n-t+1} [F(v_n(t)) - F(\underline{p})] + 1 - F(\underline{p}). \quad (6)$$

This peak comes both from accumulation of low-valuation consumers and from strategic behavior combined with perfect expectations. In particular, it increases with  $n$ , because the accumulation is more important when  $n$  is higher. During the rest of the sale, since the stock of consumers who were waiting for a low price had been emptying out in period  $n + 1$ , the demand is made up of new consumers only. Those with a valuation higher than  $\underline{p}$  have an incentive to buy immediately and the demand is thus equal to  $1 - F(\underline{p})$ .

Figure 7 summarizes the pattern of demand that should be observed if consumers had perfect foresight regarding prices.

**Prediction 1** *If consumers either perfectly foresight prices or use imperfect but time-dependent information about sales to form their expectations and take their decisions, the purchases should:*

- decrease during regular periods;

- decrease with  $\bar{p}$ , the price used during regular periods;
- increase with  $\underline{p}$ , the price during the sale;
- not depend on  $n$ , the time separating two price reductions.

## 4.2 Myopic or uninformed consumers

Let us now turn to the case of myopic consumers who do not value the future:  $\delta = 0$ . Consumers' decision is then static: they buy if and only if their valuation is above  $\bar{p}$ . Hence the pattern of purchases is flat and equal to  $1 - F(\bar{p})$  during a regular period. A similar pattern would also be observed with consumers who value the future but who do not have any information about prices, and who take their decision based on the current price only. The resulting demand depends only on  $\bar{p}$ . At the beginning of the price reduction, we should still observe a peak of demand given by:

$$[F(\bar{p}) - F(\underline{p})]\alpha \frac{1 - \alpha^n}{1 - \alpha} + 1 - F(\underline{p}). \quad (7)$$

However, and contrary to the previous case, the peak comes only from accumulation of low-valuation consumers, and not from strategic delaying of purchases. Once the stock of consumers has been emptied out, the demand during the rest of the sale is flat and given by  $1 - F(\underline{p})$ . The whole pattern is depicted in Figure 8.

**Prediction 2** *If consumers are either myopic or do not use any information about sales to form their expectations and take their decisions, the demand during periods when the price stays constantly high should stay constant and not depend on anything but the current price.*

## 4.3 Imperfect and time-independent information

We study now an intermediate and more plausible situation in which consumers have some information about prices and sales, but do not take into account that a sale is closer and/or more likely to happen as time  $t$  goes by. We say that consumers have imperfect and time-independent information. In other words, they do not revise their beliefs accordingly. To fix ideas, think of consumers believing that every period there is a probability  $\lambda = \frac{1}{n}$  that the album is on sale. They buy at  $t$  if:

$$v - \bar{p} \geq (\alpha\delta) \left[ \left(1 - \frac{1}{n}\right) (v - \bar{p}) + \frac{1}{n}(v - \underline{p}) \right], \quad (8)$$

which rewrites:

$$v \geq \bar{v}_n = \bar{p} + \frac{\alpha\delta}{1 - \alpha\delta} \frac{1}{n} (\bar{p} - \underline{p}). \quad (9)$$

The corresponding pattern of prices and purchases is depicted in Figure 9. Because the information is time-independent,  $\bar{v}_n$  does not depend on  $t$ , and there is

no declining pattern like in Figure 7. On the contrary, Figures 8 and 9 look qualitatively similar. Yet the levels of demand are different. On the one hand, myopic or uninformed consumers take their decision on  $\bar{p}$  only. On the other hand,  $\bar{v}_n$  varies with both  $\underline{p}$  and  $n$ . The higher the expected discount, the more attractive the sale and the smaller the regular demand. Similarly, when  $n$  increases, this regular demand is higher because the gain from waiting until the next promotion is lower.

The corresponding peak at the beginning of promotions is:

$$[F(\bar{v}_n) - F(\underline{p})]\alpha \frac{1 - \alpha^n}{1 - \alpha} + 1 - F(\underline{p}). \quad (10)$$

**Prediction 3** *If consumers use imperfect and time-independent information about sales to form their expectations and take their decisions, the demand during periods when the price stays constantly high should:*

- *stay constant;*
- *decrease with  $\bar{p}$ , the price used off the sales;*
- *increase with  $\underline{p}$  the price during the sale;*
- *increase with  $n$ , the time since the last sale.*

Finally, in contrast to all other *scenarii* (Figures 7 to 9), the first *scenario* (Figure 6) yields to the following prediction.

**Prediction 4** *Dynamics is relevant and important if the demand at the beginning of the price reduction is higher than at the end of the price reduction.*

This model is stylized in several respects and some extensions may be considered to make it more realistic. First, one could permit the time interval between promotions  $n$  to be random. If  $n$  were drawn from a continuous distribution  $G(\cdot)$  over  $[\underline{n}; \bar{n}]$ , one would obtain the same qualitative patterns of demand as before. In particular, in the perfect foresight case, the intertemporal trade-off would become

$$v - \bar{p} \geq \int_{\underline{n}}^{\bar{n}} (\alpha\delta)^{n-t+1} (v - \underline{p}) dG(n), \quad (11)$$

which yields to the same conclusion than previously since the RHS of (11) is still increasing in  $t$ . In the *scenario* with imperfect expectations, one would have  $\lambda = \frac{1}{\mathbb{E}n}$ , *i.e.*, consumers form now their expectations based on the *expected* time interval between promotions, and one still has:

$$v - \bar{p} \geq (\alpha\delta)[(1 - \lambda)(v - \bar{p}) + \lambda(v - \underline{p})]. \quad (12)$$

Second, one could consider a model with multiple products and introduce some probability of substituting to another product. Third, this model considers passive

or loyal customers only: an extension might consist in introducing a fraction of *shoppers* who compare prices across stores and purchase at the lowest price. A flat pattern of demand when prices are high rules out the hypothesis of forward-looking loyal customers only, which is however a common assumption in several empirical structural models.

Finally, to determine consumers' best response so far we fixed prices at the actual policy, implicitly assuming that it was the optimal policy. One can wonder what would happen if we had looked for the optimal pricing. As explained before, the latter should be composed of equilibrium prices *à la* [Conlisk, Gerstner, and Sobel \(1984\)](#) in the case where consumers have perfect foresight. On the contrary, when consumers are myopic or hold time-independent beliefs, the optimal cycle should be qualitatively similar to the one we considered. However, in practice price changes involve switching costs, or menu costs. For this reason a firm might resort to price schemes made up of high-price/low-price sequences like those observed in the data even when the optimal pricing policy is composed of more than two prices, in particular when consumers update adequately their beliefs over time. One could even think of testing whether the firm uses an optimal price strategy or not. It is yet more difficult to disentangle whether the firm is constrained by menu costs, or whether it faces consumers with time-independent beliefs. For instance, in our data a same price is charged at several occasions for many different albums, which we interpret as evidence of such menu costs.

## 5 Empirical evidence of time-independent beliefs

Previous empirical evidence is consistent with the accumulation of consumers in the market and the idea that consumers are not perfectly forward-looking. Fact 1 accounts for accumulation as stated in Prediction 4, while Fact 2 is not compatible with Prediction 1. We argue now that Predictions 2 and 3 are also testable on market-level data. First, we document empirically Fact 3 which rules out myopia (Prediction 2). Second, we show with Fact 4 that Prediction 3 is likely in our setting and that consumers behave as if they used time-independent information to form simplified expectations about the price process. For completeness, and in order to relate more precisely those facts to the theory, we propose to test directly the nature of consumer expectations from an econometric model of demand that incorporates both randomness and heterogeneity to the theoretical model exposed previously.



**Fact 3: the demand at the regular price decreases with the price gap (the difference between the regular price and the discounted price).**

We document here whether consumers are myopic, *i.e.*, whether they value the future or not. If consumers do not value the future, the demand at the regular price should be independent from the price gap  $\Delta p_{jrt} = \bar{p}_{jr} - \underline{p}_{jrt}$ . On the contrary, if consumers delay their purchases strategically, they should wait more when they expect a higher price gap, which decreases the current demand. This must hold even if they make mistakes on the timing of promotions. We estimate then:

$$q_{jrt} = \alpha \Delta p_{jrt} + \beta_x X_{jrt} + \xi_{jr} + \delta_t + \epsilon_{jrt}. \quad (13)$$

The coefficient  $\alpha$  is identified thanks to variation in discounted prices *within* an album-store. Given that  $p_{jrt}$  is equal to the regular price  $\bar{p}_{jr}$ , once  $\xi_{jr}$  has been controlled for, the unique source of variation stems from changes in the discounted price  $\underline{p}_{jrt}$ . Put differently,  $\alpha$  is identified from the observation of at least two high-price/low-price sequences with two distinct price gaps.<sup>11</sup> To allow for  $\alpha$  to be also identified through variations of  $\Delta p_{jrt}$  *across* album-stores, we estimate the model (13) imposing further  $\xi_{jr} = \xi_j + \xi_r$ .

There are two implications concerning worries about endogeneity. First,  $\Delta p_{jrt}$  is likely to be correlated with  $\xi_{jr}$  but there are less reasons to think that it is correlated with the idiosyncratic shock of demand  $\epsilon_{jrt}$ . Second, the sign of a potential correlation between the price gap and unobserved demand terms is rather ambiguous. On the one hand, popular goods may be associated with higher regular prices and lower discounts, which claims for a negative correlation. On the other hand, from a durable-good perspective, the optimal price policy consists in cutting prices when enough low-valuation consumers have been accumulating in the market (Conlisk, Gerstner, and Sobel, 1984), which moves the correlation in the opposite direction. Popular goods go less often on sales, which inflates the stock of low-valuation consumers; it may thus be beneficial to cut prices by more. To address nevertheless remaining concerns of endogeneity, we instrument  $\Delta p_{jrt}$  with  $\frac{\sum_{r' \neq r} \Delta p_{jr't}}{R_{jt}-1}$  where  $R_{jt}$  is equal to the number of stores selling album  $j$  at time  $t$ .

Table 5 shows the results. In the base specification of (13),  $\alpha = -.016$  (Column 3) while in the specification where  $\xi_{jr} = \xi_j + \xi_r$ ,  $\alpha = -.021$  (Column 4) though the equality of both coefficients cannot be rejected at 5%. Instrumenting leads to  $\alpha = -.024$  (Column 5) which is not significantly different from  $-.02$  at usual levels. These results suggest that  $H_0 : \alpha = 0$  is rejected against  $H_a : \alpha < 0$  at 5% and that this coefficient is close to  $-.02$ . Hence there is evidence of strategic delaying of

<sup>11</sup>By construction, the price gap considered here is the same for the whole high-price/low-price sequence.

purchases: consumers do take dynamic decisions in this market. However, they are neither completely myopic, nor completely forward-looking: everything happens as if they held wrong expectations about the timing of price reductions.

**Fact 4: the demand at the regular price decreases with the ratio between the price gap and the time separating promotions.**

To study now how the demand at the regular price depends on the ratio between the gain from waiting, the price gap, and the estimated time to wait, the interval  $n_{jrt}$  between price reductions, we estimate:

$$q_{jrt} = \alpha_n \frac{\Delta p_{jrt}}{\bar{n}_{jr}} + \beta_x X_{jrt} + \xi_{jr} + \delta_t + \epsilon_{jrt}. \quad (14)$$

If consumers delay strategically their purchases, they must wait more when the price gap is higher; but the longer they have to wait until the next price reduction, the less important this effect should be. As a result, we expect  $\alpha_n$  to be negative.

An empirical issue consists in determining the relevant  $n$ . Put differently, we suspect the interval between price reductions to be endogenous. To maximize revenues, a firm should put most popular albums less often on promotion. To overcome this issue we compute for each album-store  $\bar{n}_{jr} = \frac{1}{S_{jr}} \sum_{s=1}^{S_{jr}} n_{jrt(s)}$  the mean of time intervals  $n_{jrt}$  over all their  $S_{jr}$  observed “high-price/low-price” sequences. It is likely that  $\bar{n}_{jr}$  has reduced endogeneity and that informed consumers base their decision rather on  $\bar{n}_{jr}$  than on  $n_{jrt}$ . Results are displayed by Table 5, Columns 6 to 8; in the base specification of (14)  $\alpha_n$  is about  $-0.387$  and significantly different from zero at usual levels.

## Model of demand

Finally, we estimate a semi-structural model of demand that shares its main features with the theoretical model exposed before, but allows furthermore for randomness and heterogeneity. Our goal is to discriminate formally among the different *scenarii*. From the observation of demand, it is possible to separate the price effect, the part due to accumulation from the part due to consumer expectations. We still find consumers cumulate in the market and hold time-independent beliefs. In what follows we restrict our attention to album-stores having at least two consecutive “high price/low-price” sequences. This selection is motivated by an identification argument: for each album-store we need to observe at least two price cycles to disentangle the “accumulation effect” from the “anticipation effect” (see *infra*).

We introduce first some heterogeneity regarding the mass of consumers willing to purchase: we allow for cohorts to differ in size. One could imagine for instance

that a flat pattern of demand emerges as the conjunction of two phenomena: more numerous cohorts arrive systematically before promotions (increasing pattern) and hold correct time-dependent expectations (decreasing pattern).<sup>12</sup> To rule out that possibility, namely to disentangle the price effect, the accumulation part from the anticipation part in the formation of demand, we enable the size of each entering cohort  $C_{jrt}$  – the incoming demand – to depend on album-store fixed-effects  $\xi_{jr}$  as well as on week fixed-effects  $\delta_t$ . Moreover, we model accumulation as follows: considering a price reduction that lasts  $s_{jrt}$  weeks, when *during* is equal to  $k \in \llbracket 1; s_{jrt} \rrbracket$ , we assume that the incoming demand is multiplied by  $e^{\gamma_k n_{jrt}}$  where the parameter  $\gamma_k$  accounts for the accumulation of consumers waiting for low prices during  $n_{jrt}$  weeks before the promotion. Our model specifies:

$$\log C_{jrt} = \xi_{jr} + \delta_t + \sum_{k=1}^{s_{jrt}} \gamma_k n_{jrt} \times \mathbb{1}[\text{during}_{jrt} = k]. \quad (15)$$

During a regular period we impose that  $\log C_{jrt} = \xi_{jr} + \delta_t$ , while during sales the size of the cohort is multiplied by a term that increases exponentially with the time interval  $n_{jrt}$  separating price reductions, *i.e.*, the number of weeks during which consumers have cumulated in the market. The present model is therefore semi-structural in the sense that the stock of awaiting consumers is depicted by some reduced-form specification. A fully structural model would require to posit some dynamic process governing the evolution of this stock, which is beyond the scope of this paper. Consistently with Fact 1, we expect a peak at the beginning of the price reduction, which translates into  $\gamma_k$  being strictly decreasing in  $k$ . We also expect  $\gamma_k$  to be strictly positive  $\forall k$ , which indicates that the peak of demand increases with the time interval  $n_{jrt}$  separating price reductions.

Second, we make a parametric assumption on the form of consumer heterogeneity. We posit that valuations for album  $j$  are distributed according to an exponential distribution with parameter  $\mu_j$  so that  $F_j(v) = 1 - e^{-\mu_j v}$ . This hypothesis implies that valuations are album-specific, hence independent from stores, which looks like a mild restriction, and fixed over time –our restriction to old albums makes the latter assumption more realistic. Given his anticipations of the price process, consumer  $i$  with valuation  $v_i$  interested in buying the album  $j$  in store  $r$  at time  $t$  makes an intertemporal trade-off that is summarized by a threshold valuation  $\bar{v}_{jrt}$ . Purchase occurs immediately provided that consumer  $i$ 's valuation exceeds this threshold, which happens with probability  $\mathbb{P}(v_i \geq \bar{v}_{jrt}) = 1 - F_j(\bar{v}_{jrt}) = e^{-\mu_j \bar{v}_{jrt}}$ . The threshold  $\bar{v}_{jrt}$  stands for an “augmented price” that depends precisely on the nature of consumer expectations. From the theoretical model presented above, it is always equal to the current price  $\underline{p}_{jrt}$  during sales, while during regular periods it is either the current price  $\bar{p}_{jrt}$  if

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<sup>12</sup>Note however that such an explanation should hold for every price reduction. Given that promotions are album-store specific and that they do not occur at the same time, this hypothesis is rather demanding and sounds less credible.

consumers are myopic; or  $\bar{p}_{jrt} + \frac{(\alpha\delta)^{n_{jrt}-t+1}}{1-(\alpha\delta)^{n_{jrt}-t+1}}(\bar{p}_{jrt} - \underline{p}_{jrt})$  if consumers are perfectly forward-looking; or  $\bar{p}_{jrt} + \frac{\alpha\delta}{1-\alpha\delta} \frac{1}{\bar{n}_{jr}}(\bar{p}_{jrt} - \underline{p}_{jrt})$  if consumers hold time-independent expectations, where  $\bar{n}_{jr} = \frac{1}{S_{jr}} \sum_{s=1}^{S_{jr}} n_{jrt(s)}$  and  $S_{jr}$  is the number of observed “high-price/low-price” sequences. We specify thus  $\bar{v}_{jrt}$  as a function of the current price  $p_{jrt}$  and the price gap  $p_{jrt} - \underline{p}_{jrt}$ :

$$\bar{v}_{jrt} = p_{jrt} + K_t(p_{jrt} - \underline{p}_{jrt}). \quad (16)$$

The estimation of  $K_t$  enables us to discriminate among the *scenarii* above and to determine the nature of consumer expectations. If consumers have perfect foresight or revise correctly their beliefs over time (Prediction 1), then  $K_t$  must be strictly positive and decrease with the time remaining before the next price reduction. If consumers are myopic (Prediction 2) and take their decision on the current price only, then one should not reject  $H_0 : K_t = 0, \forall t$ . If consumers hold time-independent beliefs (Prediction 3), then one should obtain a positive, constant  $K_t = K > 0, \forall t$ . In the latter case we rather estimate:

$$\bar{v}_{jrt} = p_{jrt} + K_n \frac{p_{jrt} - \underline{p}_{jrt}}{\bar{n}_{jr}}. \quad (17)$$

Finally, purchases  $q_{jrt}$  result from  $C_{jrt}$  independent Bernoulli decisions with parameter  $e^{-\mu_j \bar{v}_{jrt}}$ , and thus follow a binomial distribution with parameters  $C_{jrt}$  and  $e^{-\mu_j \bar{v}_{jrt}}$ . Hence they can be approximated by a Poisson distribution with parameter  $C_{jrt} e^{-\mu_j \bar{v}_{jrt}}$  provided that the size of the incoming demand is large enough and that the individual probability of purchase is small enough:

$$q_{jrt} = \sum_{i=1}^{C_{jrt}} \mathbf{1}(v_i \geq \bar{v}_{jrt}) \sim \mathcal{B}(C_{jrt}, e^{-\mu_j \bar{v}_{jrt}}) \approx \mathcal{P}(C_{jrt} e^{-\mu_j \bar{v}_{jrt}}). \quad (18)$$

The randomness of the specification is encompassed by the Poisson distribution. Moreover, since purchases are integers, we believe that a count model is relevant in our setting. In particular, it addresses the issue of numerous “zeroes” associated with no purchase and enables us not to select them out. It allows also for a better fit of the data. Finally, in the empirical specification we keep all the heterogeneity in the price-coefficient  $\mu_j$  but constrain the term  $\mu_j K_t$  to be the same across all albums  $\mu K_t$ , which is equivalent to assume a common time pattern of the “anticipation effect” (see *infra.*) for all albums. Recovering album-specific time patterns of this anticipation effect requires to estimate many supplementary parameters and is rather demanding in terms of identification.

The estimation of the model – especially the parameters  $K_t$  – enables us to test formally for the previous predictions. It can be done by maximum likelihood: Lancaster (2000) showed that the MLE of a fixed-effect Poisson model avoids the incidental parameters problem and yields consistent estimates of all parameters

but the fixed effects. On top of that, in our setting the consistency of the fixed-effects estimates might even be achieved since we dispose of a large number of periods:  $T = 203$ .

Figure 10 leads to a clear rejection of Prediction 1, *i.e.* the *scenario* of perfect foresight, or time-dependent expectations. The pattern of  $K_t$  is not monotonically decreasing with the remaining time before the price reduction and remains rather stable over time. In particular, we do not reject the flatness at 5%. Imposing now  $K_t = K, \forall t$ , we estimate a price gap coefficient that is significantly different from zero (Table 6, Column 1). As a result, we reject  $H_0 : K_t = 0, \forall t$ , myopia and Prediction 2. From Table 6, we are prone to accept the idea of accumulation (Prediction 4). The estimated  $\gamma_k$  are positive and monotonically decreasing in *during*.

We estimate next the model under time-independent beliefs given by (17). Results are displayed in Table 6, Column 2. We find that  $K_n$  has a positive sign, in line with Prediction 3. Furthermore, we are able to quantify the magnitude of the “anticipation effect”, *i.e.*, the part due to the term  $K_n \frac{p_{jrt} - p_{jrt}}{n_{jr}}$ , which adds up to the price effect, *i.e.*, the part due to the price  $p_{jrt}$  in (17). Since the price-sensitivity parameter  $\mu_j$  varies across albums, we recover the whole distribution of anticipation effects. The median anticipation effect amounts to 16.9%: once heterogeneity in tastes, seasonal and accumulation effects has been controlled for, 83.1% of the consumer’s decision of purchase is determined by the current price (“price effect”). The remaining is due to strategic delay of purchase based on the expected gain from waiting.

## 6 Discussion

### 6.1 Potential explanations

We list here some potential explanations for our main result, the fact that consumers do not revise their beliefs as optimal, bayesian individuals would do.

Behavioral economics suggests that consumer’s rationality is bounded because of limited capacity or limited memory. Consumers may be far from *homo oeconomicus*; Simon (1955) wished to replace *homo oeconomicus* by a man with bounded rationality. More generally, the validity of the full rationality hypothesis has often been challenged. Time inconsistency (Thaler and Shefrin, 1981), hyperbolic discounting (Laibson, 1997; O’Donoghue and Rabin, 1999) or temptation (Gul and Pesendorfer, 2001) are non-exhaustive examples of non-fully rational behavior that have been widely documented both from theoretical and experimental perspectives. Ellison (2006) has pointed out that bounded rationality matters in industrial organization.

On the one hand, consumers may be unable or unwilling to do all the computations required, which refers to a limited ability of optimization. As documented

by [Vriend \(1996\)](#), “agents capabilities are constrained by perception, logical power and economic capacity”. This theory recognizes the role played by heuristics and stresses the existence of psychological biases, of the rule-of-thumb interfering with the rational decision process. [Simon \(1955\)](#) proposed an explanation based on *limited capacity*: consumers would stop their optimization once the first *satisficing* solution has been reached.

On the other hand, consumers might have a *limited memory*. They may optimize correctly, but on a restricted information set, hence reaching a second-best solution. An imperfect monitoring of the state of the world is likely because human beings are intrinsically limited in the amount of information they can receive and stock. In a similar vein, information is costly to gather ([Stigler, 1961](#)). Consumers acquire it only when it is profitable for them. As a result, they may choose deliberately not to collect further information, which bounds *de facto* their memory. Consumers may also simply forget (part of) the past. [Reis \(2006\)](#) emits the idea that consumers are *inattentive* in the sense that in multi-periods games, they do not pay attention to prices every period. [Clerides and Courty \(2010\)](#) show that in practice consumers may not pay attention to quantity surcharges,<sup>13</sup> which can also be interpreted as a lack of attention.

Finally, the heterogeneity among consumers’ degree of rationality matters. Some consumers, like occasional shoppers, dispose of little information on past prices, which might prevent them from forming correct expectations. Other consumers have access to more information, as regular shoppers do. The distinction between naive and sophisticated consumers has often been invoked by the literature. [Varian \(1980\)](#) posits heterogeneous search costs and opposes informed consumers to uninformed consumers. [Pesendorfer \(2002\)](#) distinguishes loyal, or passive consumers from occasional, or strategic shoppers. [Sobel \(1984\)](#) considers that some part of the population cannot delay strategically their purchase because of limited capacity. These forms of imperfect rationality are yet not able to fully rationalize the results obtained here.

## 6.2 Limits and extensions

First, these results are specific to the music industry where the catalogue of albums is large. As a result, the information set is big and remembering past prices of all albums is rather demanding. Moreover, there is no clear seasonality in the timing of promotions, with limited variation even at Christmas time. Even if sales are predictable and anticipating them is doable (Section 3), it is not an easy task in practice since every album has its own price cycle. The time interval between two promotions is distributed according to Figure 11 and exhibits two modes (roughly at 20 and 40 weeks) but also significant dispersion that complicates consumers’ predictions.

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<sup>13</sup>When two sizes are available, such surcharges correspond to the small size being in promotion and therefore cheaper.

Second, competition is absent from the current analysis. However it is hard to imagine that the flat pattern of demand during regular periods stems from consumers visiting systematically our retailer's rivals more at the beginning than at the end of such periods.

Third, the same test could be performed in other markets provided that prices and purchases are available over time. Consumers are probably better optimizers and form perhaps more accurate beliefs in the housing market or the automobile market where more substantial amounts of money are involved. In the clothing industry, periods of sales are determined by law (in France they occur at the beginning of January and July), such that all consumers are well informed about the timing of promotions. Yet they still differ in valuations as well as in their ability to optimize, which would enable the researcher to disentangle the limited memory explanation from the limited capacity explanation by testing specifically whether consumers optimize correctly given the public schedule.

## 7 Conclusion

This paper provides a theory and evidence attempt of testing the nature of consumer anticipations from market-level data. In a durable-good setting, when price patterns are sticky, it relates the observed demand to the kind of expectations consumer form over the price process. Strategic consumers with perfect foresight, or at least updating their beliefs correctly over time delay more and more their purchase as the price reduction approaches. Consumers with time-independent expectations also delay their purchase and wait for low prices, but this behavior does not generate a declining pattern of purchases when the price is high. In the example of music albums, we test and accept the latter *scenario*.

On the contrary, the present firm fixes prices in a dynamic fashion, and her behavior is consistent with what an optimal firm would do. Interestingly many albums of the catalogue have the same regular price, which in addition to stickiness suggests the importance of switching costs. There is room for further research to properly disentangle whether the observed high-price/low-price sequences constitute a best response to (loyal) consumers with time-dependent beliefs, or whether the firm misperceives her customers as having perfect foresight, and would resort to decreasing equilibrium price cycles in the absence of menu costs.

This paper suggests to implement the test on consumers' anticipations before the estimation of structural models of demand. Such a test would strengthen the validity of assumptions regarding consumers anticipations of the price process. Moreover, if these results do not affect the estimation of dynamic models of demand that rely already on simplifying assumptions on the price process, they do impact the firm's equilibrium price strategies and the welfare analysis as well.

A natural extension would consist in estimating a fully structural dynamic model of demand under such assumptions. It would help measuring consumer loss

due to incorrect anticipations: how much would consumers with correct beliefs gain in the current environment, *i.e.*, facing the same price process? Other issues are the computation of the equilibrium in which both the firm and consumers are perfectly forward-looking, and the comparison with actual outcomes. Finally, quantifying the gain from intertemporal price discrimination requires simulating optimal profits under uniform pricing.



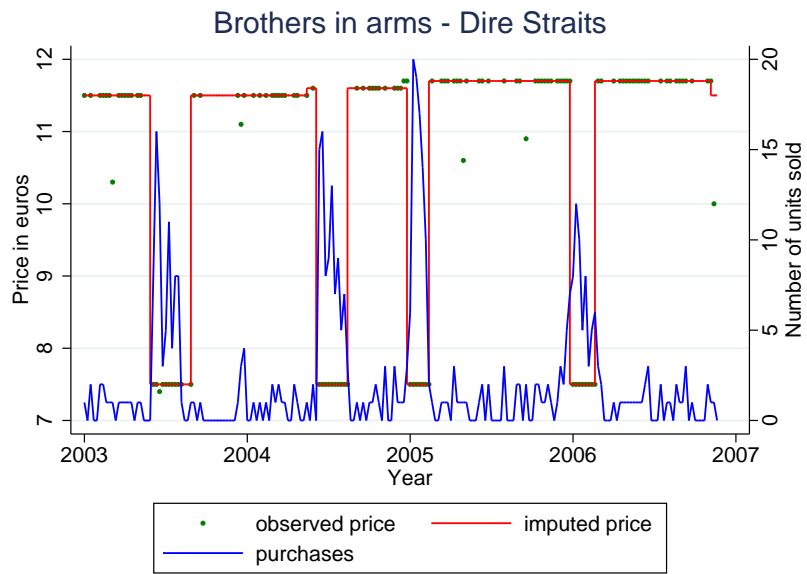
## References

- AGUIRREGABIRIA, V., AND P. MIRA (2007): “Sequential estimation of dynamic discrete games,” *Econometrica*, 75(1), 1–53.
- ANDERSEN, E. (1973): *Conditional Inference and Models for Measuring*. Mental-hygienjansk Forlag, Copenhagen.
- BAJARI, P., C. BENKARD, AND J. LEVIN (2007): “Estimating dynamic models of imperfect competition,” *Econometrica*, 75(5), 1331–1370.
- BERCK, P., J. BROWN, J. PERLOFF, AND S. B. VILLAS-BOAS (2008): “Sales: tests of theories on causality and timing,” *International Journal of Industrial Organization*, 26(6), 1257–1273.
- BOIZOT, C., J. ROBIN, AND M. VISSER (2001): “The demand for food products: an analysis of interpurchase times and purchased quantities,” *The Economic Journal*, 111(470), 391–419.
- CHAMBERLAIN, G. (1984): “Panel data,” in *Handbook of Econometrics*, ed. by Z. Griliches, and M. Intriligator. Elsevier.
- (2010): “Binary Response Models for Panel Data: Identification and Information,” *Econometrica*, 78(1), 159–168.
- CHEVALIER, J., AND A. GOOLSBEE (2009): “Are durable goods consumers forward-looking? Evidence from college textbooks,” *The Quarterly Journal of Economics*, 124(4), 1853–1884.
- CHING, A., T. ERDEM, AND M. KEANE (2009): “The Price Consideration Model of Brand Choice,” *Journal of Applied Econometrics*, 24(3), 393–420.
- CHING, A., AND M. ISHIHARA (2012): “Measuring the Informative and Persuasive Roles of Detailing on Prescribing Decisions,” *Management Science*, 58(7), 1374–1387.
- CLERIDES, S., AND P. COURTY (2010): “Sales, Quantity Surcharge, and Consumer Inattention,” CEPR Discussion paper 8115.
- CONLISK, J., E. GERSTNER, AND J. SOBEL (1984): “Cyclic pricing by a durable goods monopolist,” *The Quarterly Journal of Economics*, 99(3), 489–505.
- ELLISON, G. (2006): “Bounded rationality in industrial organization,” in *Advances in Economics and Econometrics: Theory and Applications*, ed. by R. Blundell, W. Newey, and T. Persson, Ninth World Congress. Cambridge University Press.

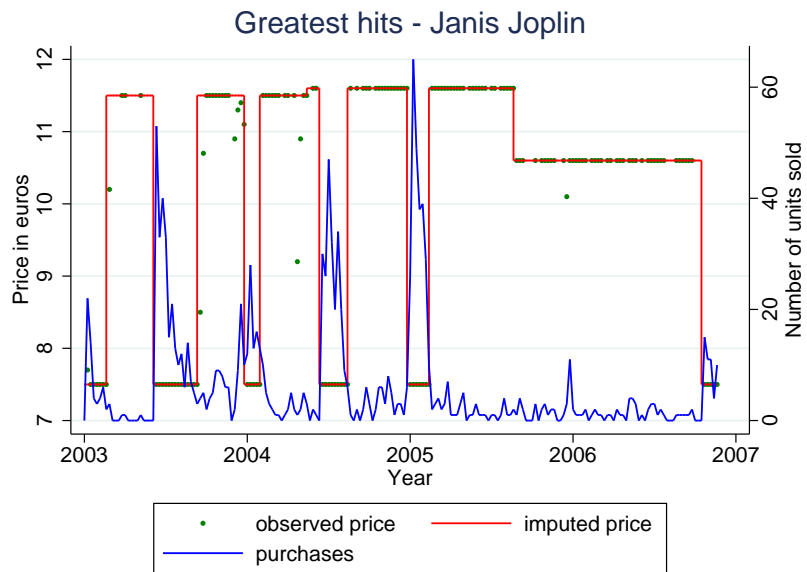
- ESTEBAN, S., AND M. SHUM (2007): “Durable-goods oligopoly with secondary markets: the case of automobiles,” *The RAND Journal of Economics*, 38(2), 332–354.
- GOWRISANKARAN, G., AND M. RYSMAN (2012): “Dynamics of Consumer Demand for New Durable Goods,” *Journal of Political Economy*, 120(6), 1173–1219.
- GUL, F., AND W. PESENDORFER (2001): “Temptation and self-control,” *Econometrica*, 69(6), 1403–1435.
- HEIDHUES, P., AND B. KŐSZEGI (2014): “Regular prices and sales,” *Theoretical Economics*, 9(1), 217–251.
- HENDEL, I., AND A. NEVO (2006a): “Measuring the implications of sales and consumer inventory behavior,” *Econometrica*, 74(6), 1637–1673.
- (2006b): “Sales and consumer inventory,” *The RAND Journal of Economics*, 37(3), 543–561.
- (2013): “Intertemporal Price Discrimination in Storable Goods Markets,” *The American Economic Review*, 103(7), 2722–2751.
- HOSKEN, D., AND D. REIFFEN (2004): “Patterns of retail price variation,” *The RAND Journal of Economics*, 35(1), 128–146.
- KAHNEMAN, D., AND A. TVERSKY (1979): “Prospect theory: An analysis of decision under risk,” *Econometrica*, 47(2), 263–291.
- LAIBSON, D. (1997): “Golden eggs and hyperbolic discounting,” *The Quarterly Journal of Economics*, 112(2), 443–477.
- LANCASTER, T. (2000): “The incidental parameter problem since 1948,” *Journal of Econometrics*, 95(2), 391–413.
- MAGNAC, T. (2004): “Panel binary variables and sufficiency: Generalizing conditional logit,” *Econometrica*, 72(6), 1859–1876.
- NAIR, H. (2007): “Intertemporal price discrimination with forward-looking consumers: Application to the US market for console video-games,” *Quantitative Marketing and Economics*, 5(3), 239–292.
- O’DONOGHUE, T., AND M. RABIN (1999): “Doing it now or later,” *The American Economic Review*, 89(1), 103–124.
- PESENDORFER, M. (2002): “Retail sales: A study of pricing behavior in supermarkets,” *Journal of Business & Economic Statistics*, 75(1), 33–66.

- PESENDORFER, M., AND P. SCHMIDT-DENGLER (2008): “Asymptotic least squares estimators for dynamic games,” *The Review of Economic Studies*, 75(3), 901–928.
- RASCH, G. (1960): *Probabilistic Models for Some Intelligence and Attainment Tests*. Denmark's Paedagogiske Institute, Copenhagen.
- REIS, R. (2006): “Inattentive consumers,” *Journal of Monetary Economics*, 53(8), 1761–1800.
- SEILER, S. (2013): “The Impact of Search Costs on Consumer Behavior: a Dynamic Approach,” *Quantitative Marketing and Economics*, 11(2), 155–203.
- SIMON, H. (1955): “A behavioral model of rational choice,” *The Quarterly Journal of Economics*, 69(1), 99–118.
- SOBEL, J. (1984): “The timing of sales,” *The Review of Economic Studies*, 51(3), 353–368.
- STIGLER, G. (1961): “The economics of information,” *Journal of Political Economy*, 69(3), 213–225.
- STOKEY, N. (1981): “Rational expectations and durable goods pricing,” *The Bell Journal of Economics*, 12(1), 112–128.
- THALER, R., AND H. SHEFRIN (1981): “An economic theory of self-control,” *Journal of Political Economy*, 89(2), 392–406.
- VARIAN, H. (1980): “A model of sales,” *The American Economic Review*, 70(4), 651–659.
- VILLAS-BOAS, S. B., AND J. M. VILLAS-BOAS (2008): “Learning, forgetting, and sales,” *Management Science*, 54(11), 1951–1960.
- VRIEND, N. (1996): “Rational behavior and economic theory,” *Journal of Economic Behavior & Organization*, 29(2), 263–285.

# Figures



(a) *Brothers in arms*, by Dire Straits



(b) *Greatest hits*, by Janis Joplin

Figure 1: Typical price and quantity patterns

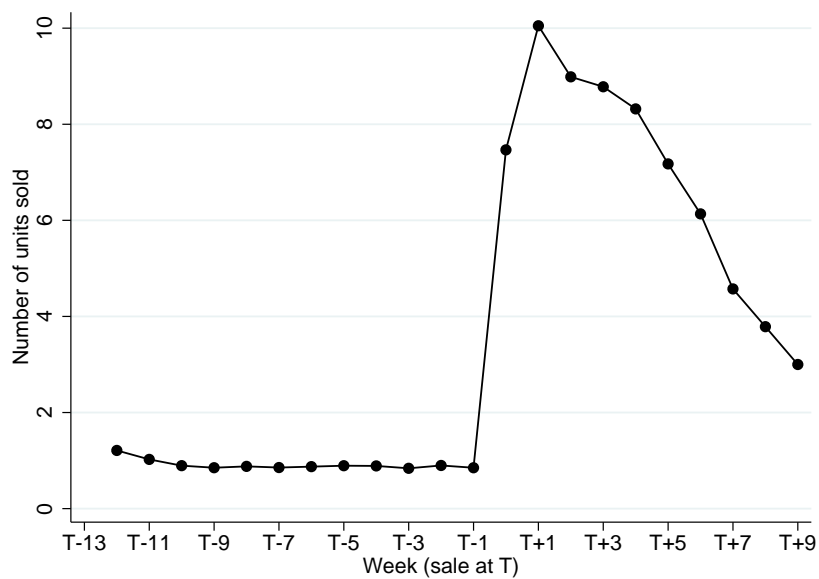
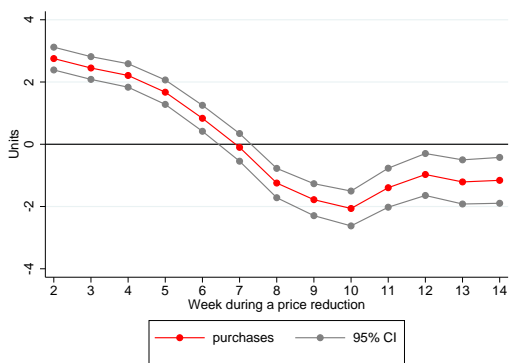
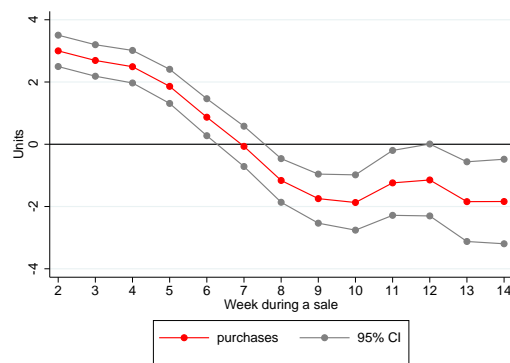


Figure 2: Average pattern of purchases

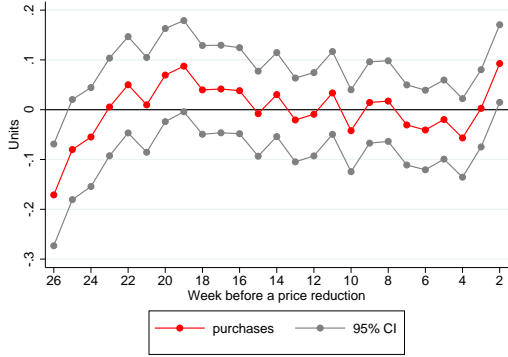


(a) price reductions

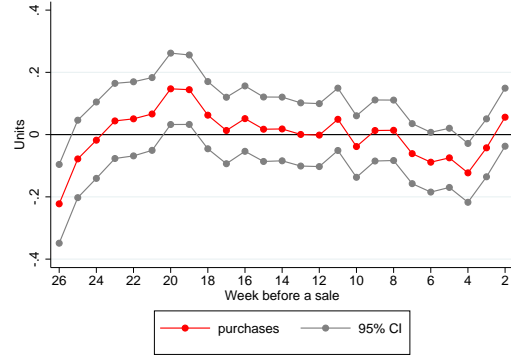


(b) sales only

Figure 3: Pattern of purchases during price reductions

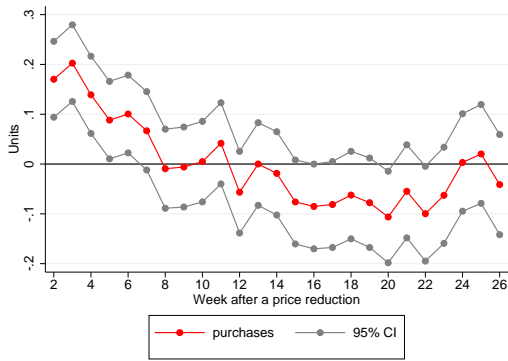


(a) price reductions

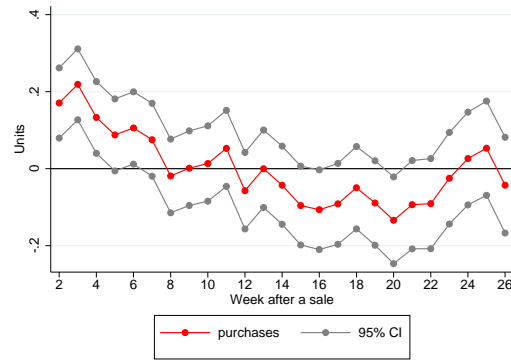


(b) sales only

Figure 4: Pattern of purchases before a price reduction



(a) price reductions



(b) sales only

Figure 5: Pattern of purchases after a price reduction

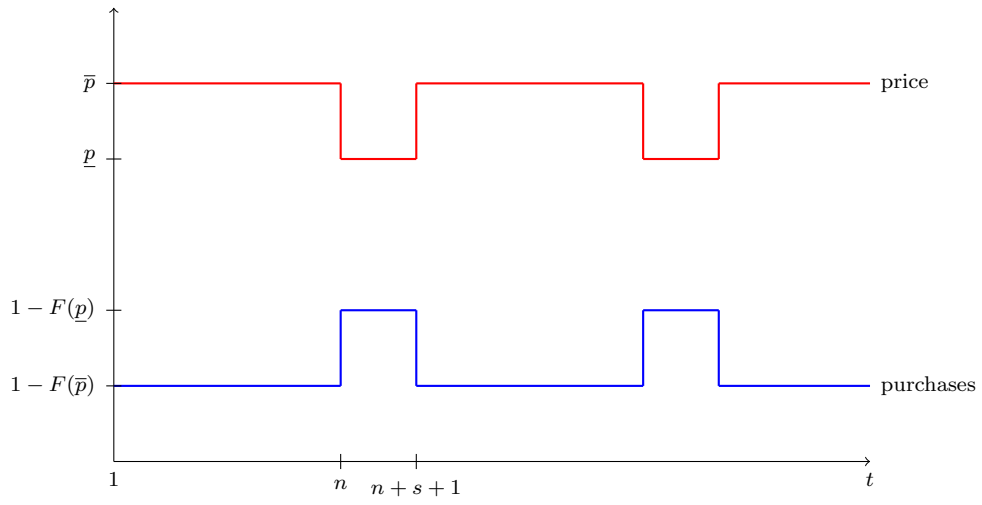


Figure 6: No accumulation

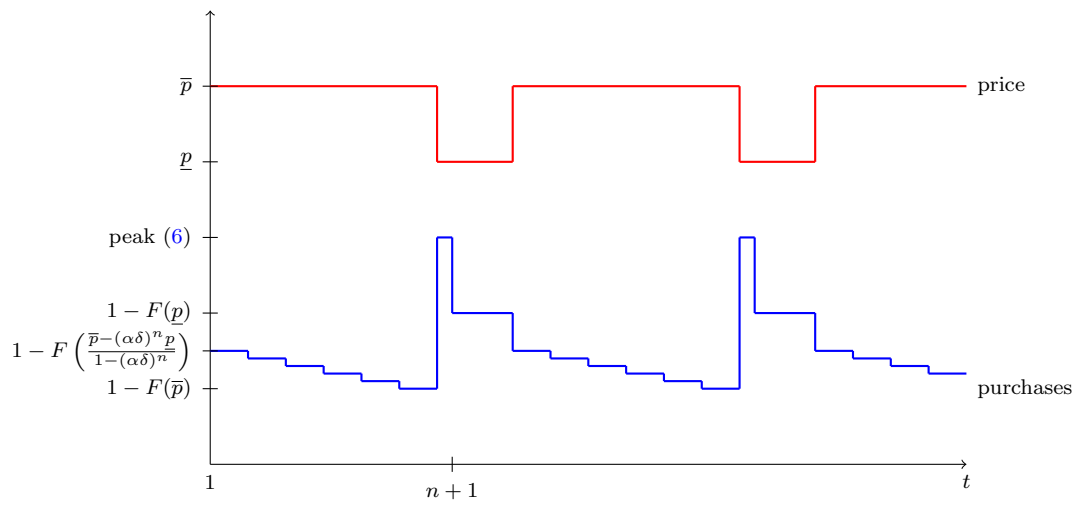


Figure 7: Accumulation and time-dependent information

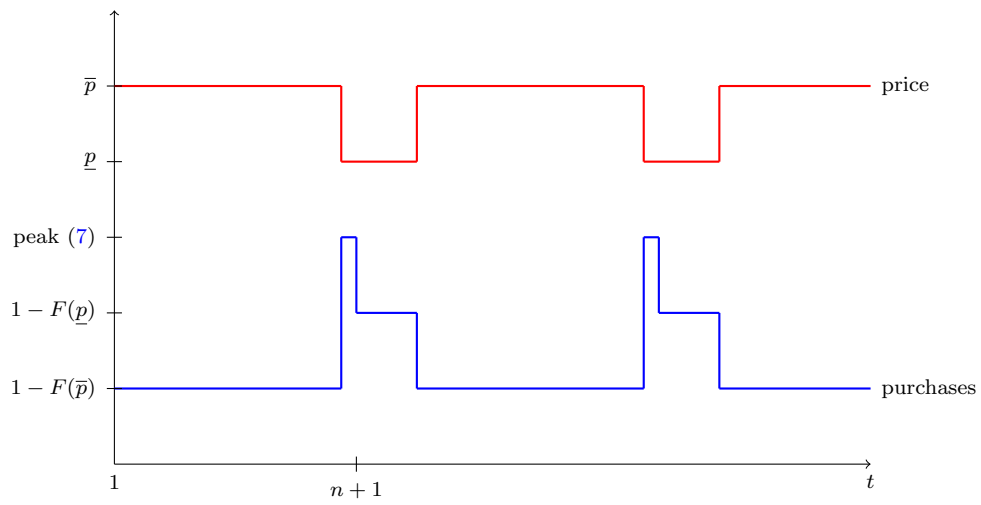


Figure 8: Accumulation and myopia

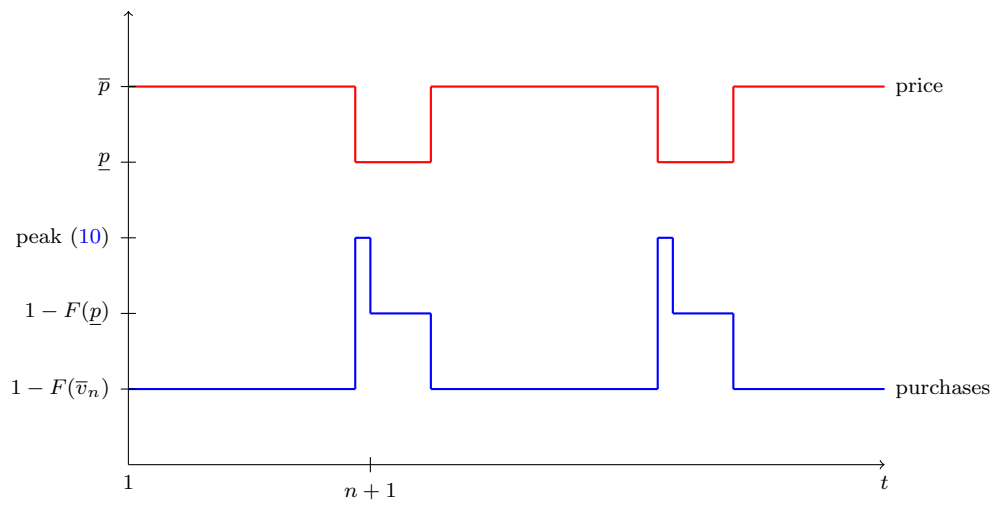


Figure 9: Accumulation and time-independent information



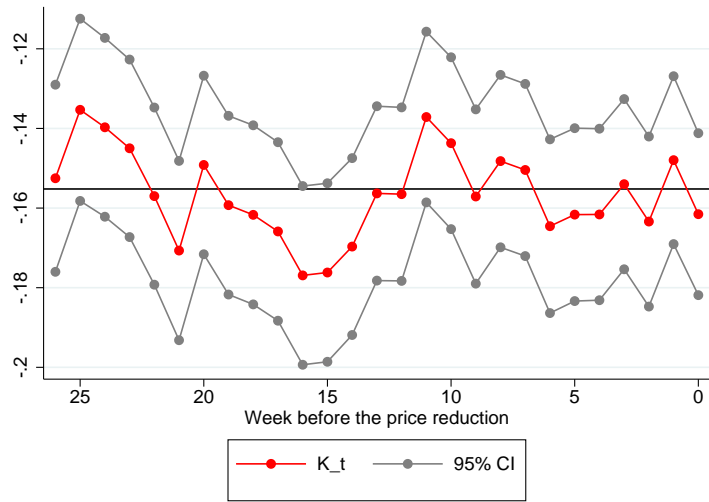


Figure 10: Evolution of the parameter  $K_t$  over time

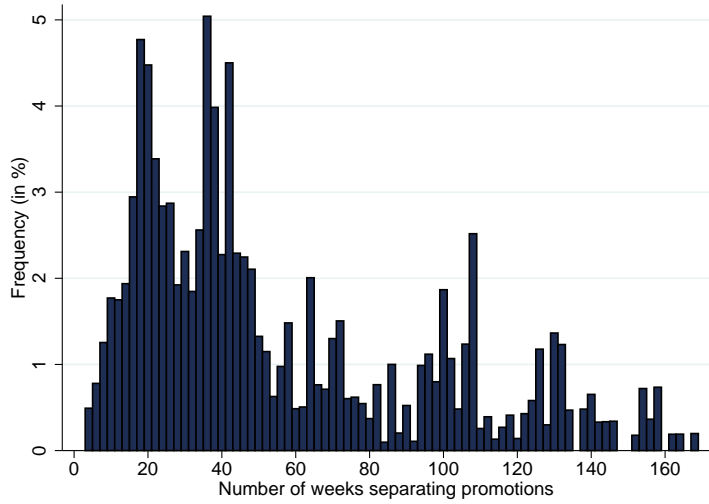


Figure 11: Heterogeneity of time intervals between price reductions

# Tables

Table 1: Prices

	Price level		# of prices per album–store	
	(1)	(2)	(3)	(4)
	Frequency	Cumulated	Frequency	Cumulated
1	61.58	61.58	0.83	0.83
2	18.64	80.22	9.11	9.94
3	8.90	89.12	22.37	32.31
4	5.46	94.58	31.07	63.38
5	3.46	98.04	20.71	84.09
6	1.46	99.50	10.52	94.61
7 to 10	0.50	100.00	5.39	100.00

*Lecture:* 8.90% of price observations correspond to the third highest price level. 22.37% of album–stores have three price levels.

Table 2: Duration of “high-price/low-price” sequences

	mean	std	min	max	med
High price	30.1	27.3	3	169	21
Low price	10.0	11.4	3	115	7
Whole sequence	40.1	31.6	6	202	30

*Sample.* 2,833 “high-price/low-price” sequences.  
*Note.* Duration in weeks.

Table 3: Price reductions: sales and durable price changes

	mean	std	min	max	med	
Regular price (in euros)	16.2	5.7	4.2	41.6	16.7	
Sales	Price (in euros)	9.9	4.9	2.5	36.7	7.5
	# of sales (per album–store)	4.0	2.3	0	11	4
	Duration (weeks)	7.4	4.3	3	60	6
	Discount (%)	37.8	15.9	5.1	79.5	37.4
	Time spent on sale (fraction, %)	14.6	9.3	0	49.3	13.8
	Revenues (fraction, %)	35.0	20.5	0	82.5	34.9
Durable price changes	Price (euros)	11.4	4.7	5	36.7	10.6
	# of changes (per album–store)	0.92	0.59	0	4	1
	Duration (weeks)	21.8	22.2	3	115	13
	Discount (%)	36.4	19.3	5.4	73.1	37.4

*Sample:* 4, 831 sales, 1, 106 durable price changes.

Table 4: Timing and length of promotions

Price reductions	Probability		Length	
	Logit		OLS	
Duration since last promotion	0.046*** (0.001)	.	.	.
Duration since last promotion $\times$ 2003	.	0.069*** (0.004)	.	.
Duration since last promotion $\times$ 2004	.	0.045*** (0.002)	.	.
Duration since last promotion $\times$ 2005	.	0.045*** (0.002)	.	.
Duration since last promotion $\times$ 2006	.	0.050*** (0.002)	.	.
$n$	.	.	0.021** (0.009)	.
$n \times$ 2003	.	.	.	0.118*** (0.048)
$n \times$ 2004	.	.	.	0.023 (0.015)
$n \times$ 2005	.	.	.	0.031*** (0.011)
$n \times$ 2006	.	.	.	-0.007 (0.016)
Album-store effects	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes
$R^2$	.	.	0.68	0.68
$\log L$	-9,897	-9,870	.	.
Observations	88,192	88,192	2,833	2,833

*Note.*  $n$  is the time separating promotions.

Table 5: Demand at the regular price

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	IV	OLS	OLS	OLS
price gap	-0.027*** (0.003)	-0.014*** (0.003)	-0.016*** (0.003)	-0.021*** (0.003)	-0.024*** (0.005)			
price gap/n						-0.693*** (0.083)	-0.387*** (0.083)	-0.116** (0.048)
# albums on promotion			-0.005*** (0.002)	-0.004** (0.002)	-0.005*** (0.002)		-0.005*** (0.002)	-0.004** (0.002)
# albums same author			0.143*** (0.010)	0.146*** (0.011)	0.144*** (0.010)		0.142*** (0.010)	0.144*** (0.011)
Album effects	No	No	No	Yes	No	No	No	Yes
Store effects	No	No	No	Yes	No	No	No	Yes
Album-store effects	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Week effects	No	Yes	Yes	Yes	Yes	No	Yes	Yes
Observations	85359	85359	85359	85359	85359	85359	85359	85359
$R^2$	0.242	0.287	0.289	0.228		0.242	0.289	0.227

Table 6: Poisson model of demand

	(1)	(2)
price gap ( $\propto -K_t$ )	-0.251*** (0.010)	.
price gap/n ( $\propto -K_n$ )	.	-1.860*** (0.097)
$n_{jrt} \times \mathbb{1}[\text{during} = 1] (\gamma_1)$	0.006*** (0.000)	0.007*** (0.000)
$n_{jrt} \times \mathbb{1}[\text{during} = 2] (\gamma_2)$	0.012*** (0.000)	0.012*** (0.000)
$n_{jrt} \times \mathbb{1}[\text{during} = 3] (\gamma_3)$	0.010*** (0.000)	0.011*** (0.000)
$n_{jrt} \times \mathbb{1}[\text{during} = 4] (\gamma_4)$	0.009*** (0.000)	0.010*** (0.000)
$n_{jrt} \times \mathbb{1}[\text{during} = 5] (\gamma_5)$	0.007*** (0.000)	0.008*** (0.000)
$n_{jrt} \times \mathbb{1}[\text{during} = 6] (\gamma_6)$	0.006*** (0.000)	0.007*** (0.000)
$n_{jrt} \times \mathbb{1}[\text{during} = 7] (\gamma_7)$	0.003*** (0.001)	0.004*** (0.001)
$n_{jrt} \times \mathbb{1}[\text{during} = 8] (\gamma_8)$	0.001* (0.001)	0.002*** (0.001)
$n_{jrt} \times \mathbb{1}[\text{during} = 9] (\gamma_9)$	0.001** (0.001)	0.002*** (0.001)
$n_{jrt} \times \mathbb{1}[\text{during} = 10] (\gamma_{10})$	-0.001* (0.001)	-0.001 (0.001)
Album-store effects	Yes	Yes
Week effects	Yes	Yes
Observations	55,439	55,439

*Note.* Observations with at least two consecutive “high-price/low-price” sequences.

# Appendix

## A Imputation of prices and smoothing

We describe here the method to recover prices when they are missing.

- Step 0: Aggregation from daily to weekly data

We follow the procedure described in [Pesendorfer \(2002\)](#) using data from the Chicago Booth GSB. The weekly price corresponds to the modal price of the week, once the distribution of prices has been weighted by purchases. We restrict our attention to the subsample of albums sold at least once during both the first two months and the last two months in every store, provided that the price exceeds 2 euros. We are left with 1,207 albums-stores during 203 weeks, *i.e.*, 245,021 observations.

- Step 1: Definition of “frequent prices”

For every album-store, from the set of observed prices we consider “frequent prices” as prices charged at least three (not necessarily consecutive) weeks. An album-store has from 1 to 15 frequent prices.

- Step 2: Imputation of frequent prices

If the difference between any observed price and its closest higher frequent price is less than the maximum of 20 cents and 2% of the observed price, we impute that higher frequent price. Otherwise, we impute the closest lower frequent price.

- Step 3: Imputation of missing prices

When there is a “zero”, *i.e.*, no purchase, prices are imputed.

- Step 3a: when there is either a one-week “zero” (20,628 observations) or a two-week “zero” (17,636 observations), we impute the maximum adjacent price.

- Step 3b: for longer periods of “zeroes” (73,205 observations), we impute the most frequent price of an album at the national level when available and when this price belongs to the set of frequent prices defined at the album-store level. Otherwise we impute the maximum adjacent price (5,230 observations).

- Step 4: Smoothing

First, we eliminate one-week price changes. Second, we eliminate two-week price changes. In both cases, we replace observed or imputed prices with the closest adjacent price.

## B List of albums

AUTHOR	TITLE	SALES	AUTHOR	TITLE	SALES
YOUNG	harvest	17735	RAGEAGAINSTTHEMACHINE	bombtrack	2662
QUEEN	platinumcollection	15469	RIVERS	johnleehooker	2582
DIDO	noangel	14269	SCORPIONS	bestof	2454
CHAPMAN	tracychapman	14264	PATRICE	ancientspirit	2430
DOORS	doors	11169	SUPERTRAMP	breakfastinamerica	2424
NIRVANA	nevermind	10000	MARILYNMANSON	antichristsuperstar	2399
LEDZEPPELIN	ledzeppeliniv	9814	SLIPKNOT	slipknot	2385
VELVETUNDERGROUND	andywarhol	9694	POLICE	reggattadeblanc	2368
CLASH	londoncalling	9677	MARILYNMANSON	hollywood	2359
HARPER	welcometothecruelworl	9559	SIMPLYRED	greatesthits	2341
SYSTEMOFADOWN	toxicity	9167	U2	war	2300
COLDPLAY	parachutes	9156	OASIS	morningglorywhatsthe	2295
PINKFLOYD	darksideofthemoon	9135	DEPECHEMODE	101live	2188
DOORS	lawoman	8594	U2	joshuatree	2116
LEDZEPPELIN	ledzeppeliniii	8069	RAMMSTEIN	liveausberlin	2012
CASAL	luzcasal	7182	MARILYNMANSON	mechanicalanimals	1976
NIRVANA	unpluggedinnewyork	7024	BAEZ	live	1972
PINKFLOYD	wall	6927	VAYACONDIOS	bestof	1948
LEDZEPPELIN	ledzeppelini	6884	WYATT	rockbottom	1940
BUCKLEY	livealolympia1995	6853	COHEN	greatesthits	1833
SEXPISTOLS	nevermindthebollocks	6795	MARILYNMANSON	smellslikechildren	1828
JOPLIN	greatesthits	6751	QUEEN	anightattheopera	1763
MADONNA	immaculatecollection	6719	POP	lustforlife	1755
PINKFLOYD	wall	6583	SINATRA	mywaythebestoffrank	1753
ABBA	abbagold	6405	BLUESBROTHERS	verybestof	1724
EAGLES	hotelcalifornia	6268	IRONMAIDEN	numberofthebeast	1723
LEDZEPPELIN	ledzeppeliniii	5959	LEDZEPPELIN	remastersvoll	1691
HARPER	fightforyourmind	5542	METALLICA	sanfranciscosymphonyor	1691
CONTE	bestof	5495	JOPLIN	pearl	1683
PINKFLOYD	wishyowerehere	5335	COLLINS	serioushits	1683
LOVE	foreverchanges	5236	CROSBYSTILLSANDNASH	dejavu	1664
COLLINS	hits	5224	DOORS	bestof	1589
PINKFLOYD	atomheartmother	5211	PINKFLOYD	more	1567
REDHOTCHILIPEPPERS	californication	5209	SMITH	easter	1553
DYLAN	essentialbobdylan	4949	REED	berlin	1497
SYSTEMOFADOWN	systemofadown	4917	ZZTOP	greatesthits	1419
BEATLES	bleu19671970	4523	KSCHOICE	paradiseinme	1408
DOORS	waitingforthesun	4380	BEATLES	rubbbersoul	1365
WHO	whosnextremasterise7	4365	WAITS	mulevariations	1302
SMITHS	queenisdead	4180	HENDRIX	axisboldaslove	1297
DEEPPURPLE	madeinjapan	4080	MADONNA	ultimatecollection	1275
BEATLES	sergentpepperslonelyh	4003	SIMPLEMINDS	liveinthecityoflight	1271
BEATLES	whitealbum2cd	3926	POGUES	verybestof	1262
MADONNA	music	3912	SANTANA	abraxas	1213
BEATLES	rouge19621966	3748	WHO	liveatleeds	1211
RAMMSTEIN	mutter	3682	QUEEN	newssoftheworld	1165
CLAPTON	unplugged	3577	SOMERVILLE	greatesthits	1093
BEATLES	abbeyroad	3508	MAMASANDTHEPAPAS	verybestof	1043
HENDRIX	electricladyland	3473	BEATLES	help	1035
PINKFLOYD	meddle	3376	MARILYNMANSON	lastfour	1021
HENDRIX	experiencehendrix	3326	QUEEN	innuendo	994
DIRESTRAITS	brothersinarms	3237	NOMI	20plusbelleschansons	982
PINKFLOYD	animals	3171	MARILYNMANSON	portraitofanamericanf	905
REDHOTCHILIPEPPERS	bloodsugarsexmagik	3159	QUEEN	livemagic	819
HARPER	willtolive	3147	KNOPFLER	sailingtophiladelphia	731
STEVENS	teaforthetillerman	3129	TYLER	bestof	688
ROLLINGSTONES	flashpoint	3052	ZAPPA	hotrats	686
RAMAZZOTTI	eros	3026	BUCKLEY	sketches	639
MADNESS	onestepbeyond	2840	CARPENTERS	gold	588
JETHROTULL	aqualung	2723	KNOPFLER	neckandneck	504
SUPERTRAMP	verybestofvoll	2720			