How social comparison influences reference price formation in a service context

ABSTRACT

What is the influence on reference price when the source of price information is anonymous versus social? This article investigates the formation of reference prices given an observed sequence of past prices in a service context. An experimental study suggests that, considering the same price information, if the source is social (i.e., the prices paid by colleagues), then consumers want to pay less. More specifically, social comparison changes the way individuals weigh information, attributing more importance to the lowest historical prices and to the range in price variations.

Keywords: reference price, social comparison, dynamic pricing, Prelec weighting function

1. Introduction

Imagine you want to book a hotel room. Some weeks in advance, you check prices on the Internet. Because of dynamic pricing practices, you are accustomed to seeing variability every time you check for a price. To judge whether the offered price is a "fair deal", you recall past prices you might have seen or paid for this or a similar service. Alternately, friends or colleagues may have informed you of how much they paid for the same hotel. The amount you or others have observed/paid in the past influences your reference price, which can be considered the basis to judge the deal you are offered.

Research over the last 30 years corroborates that reference points dramatically affect people's decisions. According to psychologists (Lewin et al., 1944; Siegel, 1957), reference points are often defined as the decision maker's status quo or as an expectation. Kahneman and Tversky (1979) transferred the concept of reference dependence from psychology to behavioral economics, explaining that people frame outcomes as gains or losses relative to relevant reference points. The relevant literature examines the effect of reference points in the price domain, that is, on reference prices (Briesch et al., 1997; Mazumdar et al., 2005), and the topic relates to research on new pricing mechanisms, such as bidding behavior (Wolk & Spann, 2008) and pay-what-you want pricing (Johnson & Cui, 2013).

Two main conceptualization models are available on reference price. The most common is that reference prices are predictive price expectations. This model, named the expectation-based reference price, is derived from adaptation theory (Helson, 1964) and implies that people judge a stimulus in relation to the level to which they have adapted (Mazumdar et al., 2005). In a second model, reference price is a normative price, that is, the price considered as fair for the seller to charge (Bolton et al., 2003; Campbell, 1999). Both economic and social components have been shown to affect evaluations of price fairness. The conceptualization used generally depends on the market, customer group, and product/service involved.

The way people form their reference price becomes particularly relevant in contexts where favorable conditions for price discrimination occur, as consumers can easily pay a different price for the same product or service. Accordingly, price comparison is a consequence of dynamic pricing or price discrimination. Although several studies suggest that time-based pricing strategies tend to be accepted by consumers, price discrimination may be perceived as unfair if standard conventions are violated (Huang et al., 2005; Wirtz & Kimes, 2007). Social comparison theory (Van den Bos et al., 1998) offers a potential underpinning for some of these results and highlights a possible threat for the acceptability of these pricing strategies. The awareness that another similar consumer paid a lower price appears to be a particularly potent source of perceived unfairness (Haws & Bearden, 2006), a factor that may reduce the reference price.

Research has not revealed a direct elicitation of reference prices in a time-based pricing context between different sources of information. Thus, our goal is to determine if the source of information of past prices, whether social (i.e., prices that friends or colleagues have paid for a similar product or service in the past) or anonymous (i.e., market prices the individual has observed in the past), can influence the formation of the reference price in its normative conceptualization. This study creates several scenarios where different prices for the same service (a hotel room reservation) become available, seeking to elicit the impact of past price information on reference prices. More precisely, Section 2 discusses the theoretical underpinning of the research hypotheses. Section 3 then uses an experimental setting to investigate whether the same price sequence can produce a different reference price depending on the source of information (social or anonymous) and how individuals attribute weights to past information that can predict the reference price. Finally, Section 4 discusses the results and their managerial implications.

2. Background

2.1. Reference price and social comparison

All price evaluations evoke some form of comparative judgments (Xia et al., 2004). This perspective relates to the general idea that much of people's understanding of themselves is not context-free but rather is based on similarities within their environment. People compare what others from a similar social group paid for the same service or product, especially when prices vary across consumers and lack transparency (Mezias et al., 2002). This social comparison process is likely to substantially affect reference prices.

Social comparison is important for evaluating fairness as a means of distributive justice (Van den Bos et al., 1998). Because it is difficult to gain an accurate appraisal by comparing dissimilar others, social comparison is largely directed towards a referent group (Festinger, 1954). When people compare their outcomes with similar peers, shared attributes do not help them to make an evaluation. For this reason, people tend often to focus on information that supports the dissimilarities. In other words, people experience greater satisfaction from a purchase if they paid less than a peer. These concepts of downward social comparison and upward social comparison have solid roots. Wills (1981) introduced the concept of downward social comparison to identify situations where people look at others who are worse off to increase their own sense of well-being. With respect to upward social comparison, people compare themselves with those who are better off so as to belong to a superior group (Collins, 1996).

In contexts where social comparison is strong, the comparison of dissimilarities is amplified, thereby increasing sensitivity toward unfairness (Xia et al., 2004) and loss aversion (Kahneman et al., 2005). Social justice literature also notes that the fairness of a process affects the way by which people self-evaluate (Brockner et al., 2003). Among the three motives of self-evaluation (Sedikides, 1993), two have been found to be particularly impactful when people look badly by social comparison. These two motives are self-enhancement (Wood, 1989) and self-assessment (Oliver & Swan, 1989). In particular, Scholl et al. (1987) show how other's pay can be a relevant part of pay dissatisfaction, involving appraisals of inequity and injustice. Thus, even when a consumer pays the reference price, information that another customer paid less leads to perceptions of unfairness.

Other consumers' prices are generally considered an unequivocal standard for what focal consumers deserve to pay. Ashworth and McShane (2012) show that paying more than another consumer enhances reactions of unfairness by making the violation of what is deserved especially salient and disrespectful. In other words, paying more than a *peer* is interpreted as a personal affront.

Accordingly, comparisons with similar others are expected to produce lower reference prices, which leads to the following hypothesis:

H1. Comparisons with peers produce lower reference prices due to an increased sensitivity towards unfairness.

2.2. Reference price formation over time

In natural environments, purchasing decisions have a temporal dimension, which means individuals usually form their reference prices after observing sequences of prices (Bell & Lattin, 2000). In other words, they collect different pieces of available information (Thaler, 1985), which in our case originate from market prices observed in the past (anonymous source) or from prices actually paid by others belonging to the same social group (social source). It is then necessary to investigate the way the source of the information interacts with other factors that characterize the formation and updating of reference prices. Building on the previous literature, this article identifies some factors in sequences of past prices that can affect the current reference price. These factors include the first, the average and the last price seen; the highest and the lowest price; and the variability and trend of the sequence of prices.

First, average and last price. Dickson and Sawyer (1990) conducted a field study and found that the further in the past a certain price is, the less it contributes to the current reference price. Therefore, reference prices are often represented as a decaying weighted average of all past prices.

The last price, as in Nasiry and Popescu (2011), is assumed to be the most influential. Baucells et al. (2011) found that, in a financial setting, the first price has an important weight in the formation of reference prices. In their study, however, the first price was also the investor's purchasing price.

Highest and lowest price. Kahneman et al. (1993) were the first to introduce the magnitude of past peaks in the evaluation of a sequence. In consumer prices, while the lowest price seems to be an important cue for reference prices (Ackerman & Perner, 2004; Rajendran & Tellis, 1994), high prices are also important because of loss aversion (Novemsky & Kahneman, 2005). Cowley (2008) shows that people tend to evaluate past experiences giving a retrospective evaluation from the proverbial "rose-colored" glass, thus suggesting *good news*. In this article, the presence of a low price paid for something in the past is given significantly more weight than personally irrelevant information.

The trend. Based on the order of the events in the timeline, the trend also influences the overall evaluation. In the financial context, Grant, Xie and Soman (2010) show that investors update reference points asymmetrically in that they more quickly adapt their reference points to good news, i.e., an increase in the value of a stock, and more slowly adapt to bad news. Baucells et al. (2011), while they do not find evidence for asymmetry in the speed of adaptation, find instead an optimistic shift in expectations, which may explain why people are more easily disappointed than they are elated.

The variability. Related to the magnitude of prices, variability affects reference price. Distributive justice and the principle of loss aversion play a role when differential prices or customer treatments are examined from the perspective of the consumer. This is even more relevant in the service industry where the use of dynamic pricing is intense. Although there is a smaller degree of perceived unfairness when the inequality is to the disadvantage of other consumers (Mayser & von Wangenheim, 2012), consumers are hesitant to accept and absorb different prices. For this reason, they lower their reference price (Drechsel & Natter, 2011) and then wait until the product or the service is found at the lowest price (Suk et al., 2012).

More formally, we derive the following hypotheses:

H2a. When eliciting a reference price from a sequence of past prices, first and last price, as well as lowest and highest price, affect reference price formation more than other price information.

H2b. Trend and variability capture the overall impact of both timeline (first and last price) and magnitude factors (lowest and highest price).

The joint consideration of social comparison and factors influencing reference price formation over time leads to an additional hypothesis. Several studies highlight that in a social comparison context knowing that another consumer paid a lower price immediately adjusts the reference price negatively and influences price evaluations more than a variety of other price-equivalent comparisons (Mazumdar et al., 2005; Haws & Bearden, 2006). Thus, by sequences of past prices, the social source of information should reduce reference prices because comparisons with similar others increase the importance of lowest prices from the perspective of the consumer. Indeed, the source of information may change the way people weigh past information.

Many authors have operationalized reference price as a weighted average of past prices (e.g., Nasiry & Popescu, 2011; Baucells et al., 2011). This article builds on this literature by highlighting that in a social environment people mentally weigh previous information based on order of magnitude (from the lowest to the highest price information) rather than on order of time (from the first to the last information received).

H3. The relative importance of factors behind reference price formation differs depending on whether the source of information is anonymous or social.

> *H3a. In the presence of social comparison, forecasting models framed by magnitude rather than by timeline predict reference prices with greater accuracy.*
>
> *H3b. In the presence of an anonymous source, forecasting models framed by timeline rather than by magnitude predict reference prices with greater accuracy.*

3. Experimental study

Consider a consumer who observes a sequence of prices P_i, $i = 1, \ldots, n$. She observes one unit of a product in period 1 at price P_i, thus forming an initial reference price. In the subsequent periods, she observes the other pieces of information and therefore has the opportunity to update the reference price.

While the majority of earlier studies infer reference price indirectly by observing choices, there is a recent tendency to elicit and measure the reference price directly. Different researchers adopt different conceptualizations, different measurement techniques and different interpretations of the reference price. Rajendran (2009) proposes a distinct operationalization of the reference price depending on whether its conceptualization is based on the notion of the expected price or the fair price. While the expected reference price is elicited as the "estimate of the likely price", the fair reference price is elicited as "a price above which it would be too high and below which it would be a good deal".

This article elicits reference prices within the fairness conceptualization of the reference price because, as shown by Rajendran (2009), consumers appear to be increasingly concerned with fairness and good value when reference prices are retrieved from past prices. Arkes et al. (2008) and Baucells et al. (2011) investigate changes in reference points using a similar fairness-based question. For this reason, in the experiments, participants have to state the price "fair for the reservation, meaning neither expensive nor cheap".

Aside from measuring the average impact of social comparison (H1), the study is designed to investigate the joint effect of the discussed explanatory factors in sequences of past prices (H2a and H2b). Furthermore, the study sheds light on how people mentally weigh previous prices depending on the source of information (H3, H3a and H3b).

3.1. Method

3.1.1. Participants

Participants in the study included 60 undergraduate students, 32 females and 28 males, from a course in business administration at Pompeu Fabra University who accepted an invitation to register for the experiment via e-mail. The average age of the participants was 21 years, and the range was from 20 to 26 years. Participants received a fixed payment of €5 for their participation.

3.1.2. Instructions and procedure

To conduct the experiment, the following situation was created. Participants were told that they would have to observe a sequence of prices charged by a unique hotel in a village; they were given no additional information. There was a four-second delay before each new price was added to the sequence from first price to last price. The length of each sequence of prices varied between 3 and 8 periods. The total number of sequences presented to participants was 120, and the order of the sequences presented was randomized.

Participants were randomly allocated to one of two groups: an anonymous group and a social group. In the anonymous condition, participants were asked to imagine that the observed prices were prices found while surfing the Internet:

"You already checked the Internet for the unique three-star hotel of the village and you found a different price offer every four days (the reservation cannot be traded)".

In the social condition, participants were asked to imagine that the prices shown were the prices paid by colleagues in the past:

"Your close colleagues at work join you. They have already bought their reservation (...). Every four days, one colleague told you the price that he or she paid for the reservation".

The question for both groups was the same.

"Only after observing the different prices – you have no other information on how much a reservation in that city costs – you ask yourself what price you would think is ***fair*** *for the reservation, meaning you feel it is* ***neither expensive nor cheap****".*

The predesigned sequences (see Appendix) are plausible samples of the process described and were presented to the participants in random order. The variations within series are consistent with the use of dynamic pricing in the hoteling industry (Abrate et al., 2012).

Before receiving the financial compensation, students were asked to indicate on a 1 to 5 scale whether the instructions were clear where 1 equals completely unclear and 5 equals completely clear. The average score across the 60 participants was 4.0. Thus, it is reasonable to assume that participants understood the presented procedure. The average processing time was 40 minutes.

3.1.3. Experimental Design

The experiment follows a mixed model design. The source of price information (social or anonymous) is investigated as a *between-subjects* variable, and participants were randomly split into one of the two conditions. As *within-subjects* variables, the experiment accounts for all timeline and magnitude factors discussed in Section 2.2; that is, the first, the average, the last, the highest and the lowest price as well as the trend and the variability. In principle, to disentangle the impact of each single within-subjects variable, one could design pairs of orthogonal sequences, i.e., pairs of identical sequences with respect to all studied factors but one. In this situation, however, some factors are partially overlapping. Specifically, it is not possible to design a pair of sequences perfectly orthogonal to the trend. If we fix the last price, then we must have two distinct first prices – see, for example, sequences 1-2 and 3-4 in the Appendix. If we fix the average, we must modify both the first and the last price – see sequences 13-14. Furthermore, by changing the lowest (or highest) price and maintaining a constant average, the standard deviation of the sequence also changes. This requires that we go beyond the strict comparison of pairs of sequences by exploring multiple factors simultaneously.

The final design consists of 120 price sequences, as shown in the Appendix. The sequences are divided into three homogeneous blocks of 40 sequences, and each of the 60 participants participates in one single block. Therefore, each participant sees 40 sequences presented in random order.

3.2. Empirical analysis

After considering the general difference between the anonymous and social conditions, the study estimates weighting regression models by sorting sequences according to timeline and magnitude. A Prelec weighting function (1998) then provides an integrated model to predict reference prices. This function investigates the effect of each piece of information when a new element in a sequence unfolds. Finally, the study investigates the predictive power of these different approaches by comparing them with the simple average of the sequence, a naïve method suggested as a benchmark in the forecasting literature (Armstrong, 2012).

3.2.1. Weighting regression models

We explicitly separate the influence of the factors of timeline and magnitude, recognizing two alternative ways to sort price information:

- the first is to sort each sequence of *n* prices by timeline (T), thus keeping the price order as it was shown to participants, from the first to the last period: $P_1^T, P_2^T, \dots, P_i^T, \dots, P_n^T$
- the second is to sort the same sequences by magnitude (M), rearranging the sequence of prices from the lowest (P_1^M) to the highest (P_n^M), thus yielding the following order: P_1^M, $P_2^M, \dots, P_i^M, \dots, P_n^M$

In both cases – timeline and magnitude – reference price is a weighted average of past information, where, by construction, the sum of weights is equal to one and each price in the sequence P_i^T (P_i^M in the case of magnitude) has a non-negative weight π_i^T (π_i^M). Such weights can be estimated by means of linear regressions after imposing the proper theoretical constraints over the parameters, such that $\sum_{i=1}^{n} \pi_i^T = 1$, with $\pi_i^T > 0\ \forall\ i=1,2,\dots,n$ in the case of timeline sorting and $\sum_{i=1}^{n} \pi_i^M = 1$, with $\pi_i^M > 0\ \forall\ j=1,2,\dots,n$ in the case of magnitude sorting.

Regardless of the length of the sequence, the study identified three explanatory variables: the first (lowest) price, the average of intermediate values, respectively, for timeline and magnitude, $\mathrm{INT}^{\mathrm{T}} = \sum_{i=2}^{n-1} \frac{P_i^T}{n-2}$ and $\mathrm{INT}^{\mathrm{M}} = \sum_{i=2}^{n-1} \frac{P_i^M}{n-2}$, and the last (highest) price. This leads to two alternative models of reference price formation.

MODEL 1 (TIMELINE): $R = \beta_0^T + \pi_1^T P_1^T + \pi_{Int}^T\ \mathrm{INT}^{\mathrm{T}} + \pi_n^T P_n^T$ [1]

MODEL 2 (MAGNITUDE): $R = \beta_0^M + \pi_1^M P_1^M + \pi_{Int}^M\ \mathrm{INT}^{\mathrm{M}} + \pi_n^M P_n^M$ [2]

In addition, this study proposes a third parsimonious model that allows testing H2b. In model 3, the factors explaining reference price are the average (AVG), the price variability, which is measured as standard deviation (SD), and the trend (TREND), which is computed as the difference between the average of prices in the second half of the sequence and the average of prices in the first half of the sequence. Both Models [1] and [2], in the case of equal factor weights, predict the same reference price, i.e., the average. Then, consistent with H2b, the trend can capture the presence of different weights across timeline factors, while, in parallel, price variability can capture the role of magnitude factors.

MODEL 3 (MIXED): $R = \beta_0^{MIX} + \pi_{Avg}^{MIX}\ \mathrm{AVG} + \beta_{Tr}^{MIX} \mathrm{TREND} + \beta_{Sd}^{MIX}\ \mathrm{SD}$ [3]

3.2.2. The Prelec Weighting function

A more comprehensive approach is to rewrite reference prices as a function of *all* observed prices and define a cumulative weighting function, w:[0,1] → [0,1] (strictly increasing and where w(0)=0 and w(1)=1). As in Baucells et al. (2011), the model is based on the Prelec function (1998). Defining *n* as the length of the sequence, *i* as the position of the price in the sequence (i = 1, 2, …, n), either sorted by timeline or magnitude, and *w* as the cumulative weight attributed to all prices from 1 to *i*, the formal analytics are as follows:

$R = \sum_{i=1}^{t} \pi_i \cdot p_i$ [4]

$w\left(\frac{i}{n}\right) = \sum_{j=1}^{i} \pi_j$ [5]

$$w\left(\frac{i}{n}\right) = e^{\frac{-(-\ln(\frac{i}{n}))^{\gamma}}{\delta}} \qquad [6]$$

The Prelec function [6] depends on two parameters. The first parameter, γ, controls for the curvature of the weights such that the lower the parameter, the greater the weight given to the extreme values, first and last in the timeline case and lowest and highest in the magnitude case. The second parameter, δ, controls for the elevation such that the lower the parameter, the greater the weight given to the first (lowest) price at the expense of the last (highest) price.

Using a two-step approach, the study first estimates equation [4] to derive the cumulative value weights of [5], thus estimating separated regressions for each of the various lengths of the sequences (n = 3, 4, 5, 6, 7, 8)[1]. The second step uses the different weights obtained for each sequence length to estimate the two-parameter weighting functions. By using a logarithm transformation of [6], the estimation of the parameters can be obtained by means of linear regression:

$$\ln\left(-\, ln\left(w\left(\frac{i}{n}\right)\right)\right) = -\ln(\delta) + \gamma * \ln\left(-\, ln\left(\frac{i}{n}\right)\right) \qquad [7]$$

3.2.3. Results

A first analysis measures the average impact across sequences of the source of information on the reference price (H1). If prices are presented as those paid in the past by colleagues/friends rather than as prices asked on an online booking system, then participants, on average, significantly lower their reference price, 117.39 versus 137.98, ($t(1199) = 25.79$, $p < .001$). As noted in the Appendix, this evidence extends to the vast majority of sequences analyzed (104 out of 120).

[1] In some cases, especially for high values of *n*, unconstrained regressions would have led to negative estimates associated to some prices. Our solution was to impose a priori the non-negativity constraint by adapting a specific available procedure in the software Stata, named as “regprop”, which uses the maximum likelihood method.

Tables 1a and 1b document the correlation matrix of the variables to be used in the regression models.

[Table 1a and Table 1b here]

In both cases, the dependent variables (i.e., the reference prices in either the anonymous or the social condition) correlate with all the independent variables (timeline and magnitude factors). The average price highly correlates with both timeline and magnitude factors as well as with the intermediate values. First and last price highly correlate with trend (Table 1a), while the magnitude factors, high and low prices, highly correlate with variability (Table 1b). On the whole, the correlations tend to be consistent with the *a priori* models.

Table 2 provides the results of all regressions for the two conditions, anonymous and social.

[Table 2 here]

In the timeline model, the results are quite similar with respect to both the anonymous and the social conditions as the average of intermediate values is the most influential factor and the first price weighs slightly more than the last price. The latter result is coherent with the negative sign associated to trend in Model 3. The magnitude model highlights the difference between the anonymous and the social case. In the latter, the weight of the lowest price becomes dominant. The impact of magnitude factors is captured by the high effect of price variability in the mixed model, which lowers the reference price, but only in the social condition.

To test the predictive accuracy of the different models and, in turn, to highlight the predictive power of the different groups of factors the paper shows goodness of fit measures based on the R-square and the median error (Armstrong, 2012). For each model, Table 2 provides the Median Absolute Percentage Error (MdAPE) along with the Median Absolute Deviation (MAD). In the anonymous case, a clear preference towards one model does not emerge. Moreover, none of the models proposed improves the performance of the naïve predictor (the average price of the sequence), which would produce the best fit of the reference price (MdAPE = 9.091, MAD = 6.039). On the contrary, the social case presents a vastly different picture. Here, the magnitude and the mixed models perform much better than the timeline model and also perform better with respect to the naïve predictor, whose results are quite poor (MdAPE = 17.647, MAD = 10.793).

[Table 3 here]

Finally, Table 3 reports the estimates of the Prelec model for the four analyzed cases.[2] It is important to highlight that whenever the constant of the linear regression is not significant and the slope (which determines the curvature) is equal to 1, then w(x)=x. This implies that each price in the sequence has the same proportional weight and the reference price is equivalent to the simple arithmetic mean. In the case of the anonymous group, both for the timeline and the magnitude model, we could not reject the hypotheses that $\delta = 0$ and $\gamma = 1$. Therefore, in this case, the argument holds that reference price is the average of the price sequences, giving further support for the use of the naïve predictor. The same occurs in the social case when prices are sorted by timeline. However, the study obtains significant estimates both for the constant (different from zero) and the slope (different from one) for the social case with prices sorted by magnitude. Figure 1 provides a graphic representation of the weighting function. The curvature indicates a predominant importance of extreme values, with the lowest price acting as the clear main driver of the reference point. With the same average but more pronounced extreme prices, the reference decreases because of the greater weight attributed to the lowest price. This result is coherent with the previous findings, thus highlighting the negative impact of variability (see Table 2). The Prelec function, which is based on only two parameters, allows for further improvement of the prediction accuracy with respect to Models 2 and 3 (MdAPE = 8.914, MAD = 5.658).

[2] Herein we report only the estimated parameters of the Prelec weighting functions, without reporting all the first-step regressions. Detailed results are available upon request.

[Figure 1 here]

3.3. Discussion

The most striking result is the dissimilarity of the average reference price in sequences that share the same elements but differ in the source of information, social versus anonymous. Therefore, the main conclusion of the experiment is that when prices are social, reference prices are adjusted downward (H1).

The results regarding the factors guiding reference prices are more contradictory. On one hand, H2a receives little support given that models based on timeline factors do not perform better than the naïve predictor (the average price), while the magnitude models improve the accuracy of the reference prediction, but only in the social case. On the other hand, both trend and variability impact the reference price (H2b). However, only in the social case explicitly accounting for these factors can improve the predictive power of the model in comparison to the naïve predictor represented by the average price. In particular, in the social condition, the effect of past peaks is mediated by price variability that determines a strong reduction in the reference price. While Suk et al. (2012) highlighted that consumers are generally hesitant to accept variability in prices, this study defines the condition under which these results are strongly supported. This result also provides a first evidence for H3; that is, the source of information matters not only on the level of reference price but also on the level of the importance of the explanatory factors (in this case, the variability).

The regression findings along with the Prelec weighting function based on the magnitude of prices fully support H3a. In a service context with a social source of information, the predominant role of the lowest price, as well as the variability, is evident. People, aware of the presence of disadvantageous inequalities in their social environment, push for and expect to get something very close to the lowest price. Consumers' perceptions of fairness when forming a reference price in a social context are different with respect to the anonymous condition, thus moderating the goodness of models to predict the reference price. In the anonymous case, none of the proposed models improve reference prediction with respect to a simple heuristic based on the average price, and accordingly, H3b is not supported.

The Prelec approach allows for predicting reference prices with the lowest percentage error, while relying only on two parameters. Thus, results indicate that in a social context people tend to mentally order prices by magnitude and are less sensitive to the order in which these prices appeared on the timeline.

4. General conclusions

The experiment presented herein indicates that the source of information, social or anonymous, affects the formation of reference prices. This article builds on some studies regarding sequences (Ariely and Zauberman, 2000; Baucells et al., 2011), controlling in addition for the presence of social influence. The evidence suggests that when a social influence is present, people lower their reference price, while if the source of information is anonymous, people are more inclined to average past prices. People tend not to place too much emphasis on the order in which prices appeared in time, but rather give more attention to the magnitude of these prices. These findings, however, seem to be a peculiarity of the service context given that in finance (Baucells et al., 2011), people are much more influenced by the order in which prices appeared in time.

In the social case, a two-parameter weighting function based on magnitude price sorting describes the reference price formation process. Our estimates show the importance of extreme rather than central values in the price sequence, as well as the predominant weight given to the lowest – and thus more favorable – price information.

Important managerial implications for marketers that charge different prices emerge from this study. The awareness of reference dependence may facilitate the understanding of online consumer behavior while shaping pricing and discounting policies (Kopalle et al., 1996). If prices are maintained at an anonymous level, these findings suggest low prices and variability have limited influence on reference prices, thus somehow suggesting that revenue management and consumers now accept time-based pricing practices. Nonetheless boundary conditions apply in markets where social comparison is more intense because customers care about what others (from a referent group) are paying. The negative effect of social comparison on reference price highlights how preferential treatments given to some customers may induce an uneasy feeling, thereby leading to the perception of unfairness as well as the relative lowering of the reference price. Limiting the diffusion of such information, however, may not be feasible as consumers who are satisfied with their purchases tend to talk about the purchases (Brown et al. 2005) and share relevant information (Bickart & Schindler, 2001). Therefore, differences in prices must be transparent and rational. Marketers should combine price variations with customization or personalization as it will reduce comparability between transactions. Generally, it is important to separate consumers who pay less from those consumers who possess appropriate fencing conditions.

Observing sequences with extreme prices, people tend to punish for high prices (losses from a consumer perspective), giving strong weight to low prices in the determination of the reference price. This confirms one of the hypotheses from prospect theory: losses loom larger than gains. If the market consists only of loss-averse buyers and if comparisons with similar others are frequent, then the optimal strategy for firms would be to limit price variability.

The experiment involved student participants and service purchase scenarios. We are aware that presenting student participants with a hypothetical design in a lab is less than ideal. For this reason, we acknowledge that the size of these effects could be biased, and therefore, the results should be independently replicated before jumping to conclusions. Nonetheless, methodological concerns regarding the hypothetical design would, in principle, only weaken the size of the effects, while the impact of dynamic pricing may be even more pronounced when varying prices are encountered in realistic shopping online environments under conditions of higher involvement.

In the presented experiment, the past information was available on the screen. The highly weighted results of the first prices could be explained by the fact that “participants may not have clear preferences about the value of a product and rely on past prices to provide an indication of what such value is" (Sitzia & Zizzo, 2012). Nonetheless, although new online platforms present a chart of previous prices (Drechsel & Natter, 2011), if these prices are not available, memory constraints become relevant. Generally, the role of memory in recalling past prices would be an interesting research question. Aside from memory, however, reference prices are influenced by many other factors, such as decision delays, social comparisons, etc. While the study design includes many of the factors that may impact reference prices, it may have excluded others.

Future research should explore whether different price situations or different sources of social information, i.e., people higher or lower in a social rank, generate a divergent effect on reference price. The closeness of the relationship with comparison consumers should increase the sensitivity of the source of information on the reference price, thus affecting judgment regarding fairness.

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TABLES AND FIGURES

Table 1a. Correlations between timeline factors

	Anonymous	Social	First	Last	Intermediate prices	Variability	Trend	Average
Anonymous	1							
Social	0.41*	1						
First	0.41*	0.38*	1					
Last	0.29*	0.26*	-0.06	1				
Intermediate prices	0.65*	0.52*	0.23*	0.34*	1			
Variability	0.24*	-0.13*	0.03	0.18*	0.30*	1		
Trend	-0.10*	-0.19*	-0.69*	0.46*	-0.04	0.10*	1	
Average	0.66*	0.59*	0.49*	0.57*	0.88*	0.30*	-0.11*	1

* $p < 0.01$

Table 1b. Correlations between magnitude factors

	Anonymous	Social	Low	High	Intermediate prices	Variability	Trend	Average
Anonymous	1							
Social	0.41*	1						
Low	0.42*	0.69*	1					
High	0.57*	0.39*	0.34*	1				
Intermediate prices	0.62*	0.52*	0.55*	0.69*	1			
Variability	0.24*	-0.13*	-0.35*	0.66*	0.27*	1		
Trend	-0.10*	-0.19*	-0.15*	0.01	-0.15*	0.10*	1	
Average	0.66*	0.60*	0.66*	0.81*	0.96*	0.30*	-0.11*	1

* $p < 0.01$

Table 2. Multiple regression models divided by source of information

	Anonymous Timeline Model [1]	Anonymous Magnitude Model [2]	Anonymous Mixed Model [3]	Social Timeline Model [1]	Social Magnitude Model [2]	Social Mixed Model [3]
First	0.178 (0.015)***			0.295 (0.015)***		
INT^T	0.689 (0.022)***			0.521 (0.021)***		
Last	0.133 (0.016)***			0.184 (0.015)***		
Low		0.245 (0.027)***			0.688 (0.022)***	
INT^M		0.498 (0.038)***			0.236 (0.030)***	
High		0.257 (0.027)***			0.076 (0.021)***	
Average			0.807 (0.029)***			0.709 (0.023)***
Trend			-2.113 (1.324)			-4.252 (1.069)***
Variability			0.126 (0.057)**			-0.676 (0.046)***
Constant	-0.423 (0.606)	-1.762 (1.664)	22.722 (3.927)***	-20.594 (0.578)***	2.521 (1.313)	39.723 (3.169)***
Observations	1200	1200	1200	1200	1200	1200
R^2	0.45	0.43	0.44	0.36	0.51	0.47
MdAPE	9.644	9.395	9.747	11.566	9.184	9.228
MAD(MdAPE)	5.995	6.046	6.199	6.701	5.958	5.456

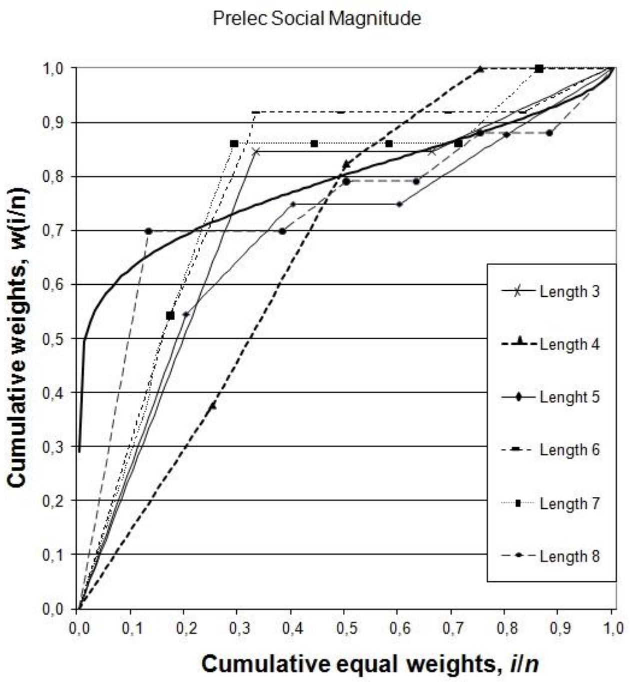
$^{*}p < 0.10$ $^{**}p < 0.05$ $^{***}p < 0.01$

Table 3. Parameter estimates of the Prelec weighting function

		Group "Anonymous"		Group "Social"	
		Timeline	Magnitude	Timeline	Magnitude
Constant	δ	1.105 (0.094)	0.966 (0.117)	0.803 (0.177)	0.274*** (0.129)
Slope	γ	1.118*** (0.104)	0.971*** (0.137)	0.915*** (0.195)	0.618*** (0.142)
H0: $\gamma = 1$. F-test (p-values)		1.29 (0.2665)	0.04 (0.8362)	0.19 (0.6653)	7.27** (0.0123)

Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Figure 1. Prelec fit



APPENDIX

Sequences used in the experiment

Seq.	P1	P2	P3	P4	P5	P6	P7	P8	Average	Average reference price Anonymous	Average reference price Social	Prelec's prediction Social
1	120	80	100						100	106.6	93.7	87.9
2	80	120	100						100	105.7	90.9	87.9
3	80	100	120						100	106.8	97.3	87.9
4	160	140	120						140	144.1	125.2	127.9
5	170	100	150						140	110.5	101.1	115.5
6	170	120	130						140	140.3	129.2	128.3
7	150	100	150	200					150	143	119.6	120.2
8	150	200	150	100					150	155.7	135.5	120.2
9	100	100	250	150					150	188.7	114.9	121.7
10	100	150	200	150					150	178	115.7	120.2
11	150	50	150	50					100	102	80.6	69.6
12	150	100	100	50					100	102.1	79.3	70.2
13	100	130	160	190	220				160	161.9	125	124.1
14	220	190	160	130	100				160	149.1	126.4	124.1
15	100	100	100	200	100				120	119.3	115.3	110.3
16	100	120	130	150	100				120	124.3	116.3	108.3
17	100	200	200	200	100				160	142.5	112.7	122.9
18	100	120	130	130	220				140	127.9	117.3	117.7
19	220	190	80	210	100				160	166.9	135.2	111.1
20	140	200	140	140	140	140			150	141.1	144.4	145.5
21	140	140	140	140	140	200			150	164.1	149.5	145.5
22	140	160	180	200	200	140			170	170.7	185.8	151.9
23	170	200	200	200	80	170			170	147.3	113.9	115.1
24	170	200	160	160	160	170			170	172.5	121.9	164.7
25	150	200	100	200	100	150			150	158.9	106.6	119.9
26	150	200	150	100	150	150			150	174.8	119.4	120.8
27	200	150	150	150	150	150	100		150	163.1	127.4	121.1
28	150	150	200	150	150	150	100		150	156.1	161.5	121.1
29	120	200	120	80	90	110	120		120	112.3	102.3	97.6
30	150	120	200	180	200	100	100		150	165.6	118	119.8
31	120	160	160	80	90	110	120		120	175.2	104.6	96.2
32	120	80	80	160	150	130	120		120	142.1	91.3	96.0
33	150	170	200	160	190	80	100		150	165.1	100.6	107.6
34	100	150	240	150	200	150	200	250	180	189	120.5	132.8
35	100	150	240	250	200	150	200	150	180	165.1	111.9	132.8
36	120	200	180	100	200	180	180	120	160	168.2	129.3	123.6
37	120	120	180	200	100	100	180	120	140	173.2	135.8	116.7
38	120	100	100	100	200	100	120	120	120	132.9	121.2	110.0
39	120	150	170	200	70	120	170	120	140	172.1	104.8	98.8
40	100	180	210	170	190	170	170	250	180	171.6	119.8	133.4
41	160	100	160						140	150.6	99.7	115.1
42	160	160	100						140	149.2	107.1	115.1
43	140	180	100						140	152.6	110.9	115.9
44	140	120	100						120	137.9	111.1	107.9
45	100	120	140						120	120.2	106.2	107.9
46	160	100	100						120	120.9	110.4	108.7
47	140	100	60	100					100	124.4	94.1	76.2
48	60	100	140	100					100	120.1	100.5	76.2
49	120	210	120	230					170	125.4	122.2	140.0
50	120	170	160	230					170	142.1	131.4	140.5
51	180	120	120	180					150	158.5	128.7	131.8
52	180	160	80	180					150	140.9	141.3	106.7
53	120	120	160	110	90				120	140.6	104	102.5
54	120	90	160	110	120				120	121.6	117.8	102.5
55	120	150	160	150	120				140	133.7	126.4	127.9
56	120	130	200	130	120				140	134.2	125.6	129.5
57	160	120	120	110	90				120	123.2	117.9	102.5
58	180	170	100	180	170				160	128	125	123.2

59	180	150	140	160	170				160	137.6	142	148.0
60	170	90	170	200	180	150			160	156.7	102.5	117.8
61	170	90	120	200	170	150			150	151.1	102.6	114.0
62	200	90	120	160	180	150			150	167.7	101.4	114.0
63	200	180	160	140	120	100			150	159.8	104.7	120.2
64	100	120	140	160	180	200			150	130	107.6	120.2
65	170	90	120	200	230	150			160	126.6	103.9	118.3
66	170	150	160	160	170	150			160	152	139.9	154.0
67	180	150	140	150	90	120	150		140	136.6	101.4	110.2
68	90	150	140	150	180	120	150		140	133.1	102	110.2
69	90	180	110	180	90	180	150		140	158.2	109.2	109.4
70	90	150	110	180	90	180	180		140	168.8	106.7	109.4
71	90	110	110	110	90	180	150		120	118.8	96.2	103.1
72	90	170	170	170	120	180	150		150	156.1	105.6	113.5
73	90	130	120	120	50	180	150		120	104.3	84.4	78.5
74	120	120	180	120	60	120	120	120	120	105.9	93.7	85.5
75	120	70	180	170	60	160	80	120	120	105.7	95.2	84.1
76	80	110	70	100	80	150	90	120	100	102.3	98.4	84.1
77	80	90	90	100	100	110	110	120	100	112.3	95	88.2
78	160	150	150	140	140	130	130	120	140	125.5	114	128.2
79	120	110	110	100	100	90	90	80	100	110	106.5	88.2
80	80	110	70	120	80	130	90	120	100	98.9	90.7	82.1
81	140	150	160						150	144.4	143.1	144.0
82	160	150	140						150	151.8	139.3	144.0
83	170	170	140						160	158.4	153.3	147.6
84	170	140	140						150	150	152	144.4
85	140	140	170						150	128.1	144.5	144.4
86	160	180	140						160	158.3	142.5	147.9
87	180	100	120	160					140	127.2	120.8	115.9
88	180	100	160	120					140	124.9	111.7	115.9
89	180	160	100	120					140	130.7	106	115.9
90	180	180	80	120					140	112.6	116.3	103.2
91	180	100	180	100					140	117.4	120.5	115.7
92	180	140	140	100					140	130.6	139.8	116.2
93	80	80	100	120	120				100	103.2	93.1	87.9
94	120	80	100	80	120				100	101.6	92.9	87.9
95	120	100	100	60	120				100	90.2	95.5	75.6
96	80	80	80	140	120				100	94.2	90.5	88.7
97	140	100	140	100	120				120	109.2	104.8	107.9
98	140	100	120	120	120				120	115.6	112.4	108.2
99	80	120	140	140	120				120	120.8	103.1	95.6
100	150	200	150	100	150	150			150	148.8	139.9	120.8
101	150	100	150	100	250	150			150	146.4	124.8	121.7
102	100	150	150	150	150	200			150	140.1	155.7	120.8
103	200	150	150	150	150	100			150	147	149.7	120.8
104	120	140	120	100	120	120			120	120.9	127.1	108.3
105	120	140	120	80	140	120			120	105.8	99.4	95.9
106	100	100	100	100	120	200			120	108.8	101.9	110.2
107	140	160	160	160	160	200	140		160	148.2	142.6	148.7
108	140	200	140	160	140	200	140		160	158.9	148.8	148.7
109	140	200	140	190	110	200	140		160	158.7	145	130.2
110	140	200	140	190	110	140	200		160	142.9	121.2	130.2
111	160	140	160	160	160	200	140		160	144.5	144.5	148.7
112	140	140	140	110	110	200	140		140	125.7	117.1	123.1
113	140	140	140	150	110	160	140		140	130.2	119.3	122.3
114	200	170	220	170	180	150	180	170	180	165.7	170.8	162.9
115	200	170	220	170	180	120	210	170	180	182.2	139.4	144.6
116	200	150	220	150	180	150	220	170	180	169.6	155.3	162.2
117	140	80	130	100	120	120	150	120	120	106.9	105.9	96.2
118	80	140	130	100	120	120	150	120	120	105.5	105.6	96.2
119	80	140	150	80	150	90	150	120	120	118.9	92.1	95.5
120	80	140	120	80	180	90	150	120	120	114.4	92.7	96.6