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Pricing

A behavioral approach

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Abstract

The research on how to determine the selling price of a product is a largely neglected field. In this study, we provide a new approach to price setting that works independently of difficult to define concepts such as 'quality of a product', which can have fluctuating definitions. Based on the work on 'approach-avoidance'-paradigms and theories on how humans perceive monetary change, we propose a price setting method based on reaction time measures that aims to assess how customers implicitly evaluate a price for a specific product. Our hypotheses are that subjects react faster to prices that extremely deviate from the normal price they would pay in a store. Additionally, we expect that they are faster for price reductions, as compared to expensive ones. Finally, we postulate that the relationship between reaction time and price manipulations can be conceptualized as an inverse U-shape, where subjects react at their slowest when seeing the retail price. Our results provide evidence for these hypotheses, suggesting that our paradigm might be used to assess how humans implicitly evaluate a specific price associated with a certain product. Looking at these results, we aspire to further refine this paradigm, and maybe provide an implicit measure of price evaluation suitable for use in a retail setting.

Keywords: price setting, market research, product evaluation, implicit measures

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The price that is set for a product has a major impact on whether one decides to buy a product or not. It thus seems sensible that if we want to unravel the impact of price setting on human decision-making, we first have to understand the human decision-making process itself. Focusing on this, the question whether humans are rational beings when it comes to decision-making is still unanswered to some extent. Research on decision-making started approximately in the Early Modern period of Europe, through the efforts of scientists such as Blaise Pascal. Pascal noticed that human beings show irrational behavior (Ore, 1960). A modern example of such irrational behavior could be participating in the lottery: the chances of winning the jackpot in the lottery in Belgium are rather slim (approximately one in eight million). Albeit the small chance of winning, we see that people partake in the lottery. Interestingly, we see a different outcome when the gamble is altered. For example, when gamblers are given a chance of one in eight million (the same chance as in the lottery) to win two hundred dollars, they will usually decline. The observation that the outcome is an important factor in decision-making formed the basis for Pascal's theory of 'expected value' (EV) (Ore, 1960). Pascal argued that the EV of a gamble depends on both the chance that the outcome occurs, and the value of the outcome. Mathematically speaking, EV is defined as a multiplication between these two factors. To illustrate the concept of EV, we return to our lottery example: the chances of winning are small, but the value associated with winning is enormous, implying that the EV (chance multiplied with value) should still be relatively large. However, in the other bet, the value of the outcome is low. Therefore, the EV associated with this gamble should be very low. Following Pascal's rationale, it makes sense that people partake in the lottery, but not in the other gamble. More generally speaking, Blaise Pascal would argue that humans are rational beings that are always looking to enlarge the EV.

If humans always make rational decisions to obtain maximal EV, then they should also be willing to pay infinite amounts of money to participate in gambles that have a certain outcome. Interestingly, this prediction is violated in a real-life setting. To explain this, we take a look at the 'St. Petersburg paradox': a paradox proposed by Bernoulli in 1738. To explain it, we slightly edited an example provided by Shafer (1988): a gambler goes to a casino and can participate in a gambling game with a starting pot of one dollar. The idea is that a fair coin is tossed, and whenever the coin lands on heads, the pot is doubled. When the coin lands on tails, the pot is returned to the player. It is beyond the scope of this introduction to provide the mathematical proof, but it can be shown that the EV of this gambling game is infinite. Following this, the theory of rational decision-making of Pascal predicts that people would pay infinite amounts of money to participate in this gamble, as the EV of this gamble is infinite. That this prediction is violated in a real-life setting is suggested by the work of Hacking (1980), who postulated that "(…) few of us would pay even $25 to enter such a game." (Hacking, 1980, p. 563). In other words, the St. Petersburg paradox shows us that EV is not the only mediating factor when it comes to human decision-making involving monetary issues.

Bernoulli (2011) extended the early work of Pascal by introducing a new theory on the concept called 'utility'. This theory postulates that the value of an outcome is not the same as the monetary value of that outcome. More specifically, Bernoulli (2011) stated that value of an outcome can be derived from a concave (i.e., an inverted U-shape) function of the monetary value of this outcome. This value conceptualization was called the 'utility' of an outcome. An example: consider the situation where two gamblers enter the same gamble. According to the theory of Pascal, their EV should be the same, as the outcome and the chance to obtain the outcome are the same for the two gamblers. However, as was pointed out by numerous researchers (e.g., Levin, 2006), the same monetary gain is perceived differently by various people: a beggar would be overjoyed upon receiving a thousand dollars, while we can assume that Bill Gates would not be ecstatic upon receiving that same amount of money. The theory of Bernoulli could account for this observation by postulating that the utility of a certain outcome depends on the person who judges the outcome. Introducing the concept of utility added explanatory power, as it allowed us to account for individual differences in perceived value of the same amount of money.

As the aforementioned theories could not account for certain violations of the utility framework (Edwards, 1954) that were still observed, new proposals with different foci than 'value' or 'utility' were suggested. One of these new models on decision-making came from Tversky and Kahneman (1974). In their work, it was hypothesized that humans use 'heuristics' to successfully execute complex judgment tasks. Kahneman and Tversky (1973) already postulated in earlier work that humans do not follow the rules of statistics and probability calculations when they are asked to make a judgment about the occurrence of certain events. Instead of thinking mathematically, they use so-called ‘heuristic principles’, which were conceptualized by the authors as simple rules of thumb that simplify the judgment task, but still yield a reasonable answer to the question. The advantage of using a heuristic is that it will provide a result that is usually a decent approximation of the actual solution, while less effort is needed to compute an answer. A disadvantage is that the heuristics can lead to systematic errors (e.g., systematic overestimations), which are called ‘biases’. Shortly after the publication of this seminal work, the research on heuristics expanded quickly (e.g., Fischhoff, 1975; Kahneman & Tversky, 1981; Tversky & Kahneman, 1983). Albeit the efforts of some researchers (e.g., Gigerenzer & Gaissmaier, 2011), no unifying model was proposed that could successfully combine all findings on heuristics into one comprehensive theory (Oppenheimer & Kelso, 2015). In summary, we argue that the research on human decision-making concerning monetary issues is extensive, but the lack of a unifying theory is compelling.

The theories on decision-making described above usually make predictions about ‘unusual choice situations’ (e.g., in the case of the St. Petersburg paradox, where the pot could infinitely double). However, these theories may also prove valuable to predict the behavior of customers in a retail setting, which is subject to the principles of decision making. Following this rationale, we will now focus on the specific literature concerning decision-making in a retail setting.

Even though the term ‘value’ again plays an important role in this research area, there is no consensus on what ‘value’ in consumer research exactly represents. Salem Khalifa (2004) for instance accurately remarked that we can divide the proposed models on ‘customer value’ into three large categories: value components models, benefits/costs ratio models, and means-ends models. Each category conceptualizes ‘value’ in a different fashion, or as Woodruff (1997) elegantly formulated it: ‘(…) even a cursory look at their definitions reveals a surprising diversity of meanings’ (Woodruff, 1997, p. 141). In the following section, we will provide a bird's-eye view of the most relevant models, and how these models conceptualize ‘customer value’. Because this study focuses more on the price paid for a product, we will only briefly dwell on the theories on ‘customer value’. For a more elaborate overview of these models and their implications, we refer to the elaborate review of Salem Khalifa (2004).

Value models

The first models we will be discussing are the ‘value component models’. In these models, it is hypothesized that the concept ‘value’ can be decomposed into ‘value elements’. To illustrate, we consider the value components model of Joiner (1994), as cited in Salem Khalifa (2004), where ‘value’ is broken down into three components. Each specific component is related to a certain need or expectation that should be fulfilled to satisfy this value component. For example, the ‘dissatisfier’ component reflects whether a basic need or service is satisfied or not. On the other end of the spectrum, we have the ‘delighters’. The ‘delighter’ component represents an unexpected service which positively surprises the customer. An example of this would be an embedded kindergarten in a supermarket, which allows parents to entrust their children to supervised care when visiting a supermarket. This service was not expected, and therefore it would not be missed if it was not available. However, the service being there would overjoy visiting parents, and thus would have a positive influence. It should be stressed that different models may differ in terms of how they look at ‘value’. To highlight this notion, we will now focus on the ‘benefits/costs ratio models’.

In this category, ‘value’ is conceived as the ratio between the received benefits, and the sacrifices the customers have made to obtain these benefits. Multiple studies (e.g., Anderson, Jain, & Chintagunta, 1992; Day & Day, 1990; Gale & Wood, 1994) hypothesized that value can be best described as a good balance between what you get and what you pay, however, some minor variation in definitions is possible. Although there are some minor differences between definitions, the general idea is the same: value is conceived as a trade-off between what one gets for the sacrifice that is made.

The last category of models we will briefly explain are the ‘means-ends models’. The name ‘means-ends models’ explains what the theory represents: the term ‘means’ signifies the products or services the customers obtain, while the term ‘ends’ represents the personal values that are deemed relevant by the customers. As was explained in the work of Huber, Herrmann, and Morgan (2001), means-ends theories argue that connections between the personal values of the customers and the characteristics of the product have an impact on how customers make decisions in a retail context. In essence, means-ends models seek to explain how customers try to reach 'end states' by buying a certain product or service.

In summary, we can argue that each type of model has its own advantages and disadvantages: the value component models describe the different concepts that together form 'value', but they neglect the sacrifice made. Benefit/costs ratio models, on the other hand, are more elaborate than value component models, but they neglect the changing nature of the value concept. Finally, the means-ends models argue that value can change, however, they lack the sacrifice component present in the benefit/costs ratio models.

When comparing the prominent theories on customer value we described earlier, we see that there are some commonalities as well (Woodruff, 1997). First of all, customer value is strongly associated with the products or services that are acquired by the customers. That is, customer value strongly depends on the considered product, and it will change when the customer evaluates different products. This is in contrast with for example personal values that stay stable across different situations (Woodruff, 1997). Secondly, as was stated in the work of Woodruff (1997), customer value has a subjective dimension, and consequentially, it is difficult to measure objectively. The final commonality is that the trade-off between what you acquire for what you give up is prominent in a lot of work on consumer value. Usually, what the customer receives is labeled 'quality' (Gale & Wood, 1994; K. Monroe, 1990), 'worth' (Anderson et al., 1992), or 'utility' (Zeithaml, 1988), while what is given in exchange is called 'sacrifice' (K. Monroe, 1990), or 'price' (Anderson et al., 1992; Gale & Wood, 1994). As we noted earlier in this introduction, the concept 'price' is of key importance for our own hypothesis. Therefore, we will now focus on the relations 'price' has with other concepts, and how 'price' has an impact on the decision-making process of customers.

Price in consumer research

When considering the impact of price on behavior, the first question one should ask is how aware customers are of prices when evaluating a product. In contrast with what would be expected, customers are generally unaware of the price they pay for a product. This result was replicated by a substantial amount of studies on price awareness (e.g., Conover, 1986; Dickson & Sawyer, 1990). More specifically, the results of these studies suggested that only 50% of the customers had an idea about the exact price of the product they bought. Dickson and Sawyer (1990) argued that an explanation might be that customers do have an idea about the price when they initially select a product, but this representation of the price is forgotten shortly after the acquisition of the next product.

Even more surprising is the finding that customers remained unaware of the prices even when a discount was offered on a product. In the study of Dickson and Sawyer (1990), more than half of the clients were unaware of the fact that they just selected a product which was selling at a reduced price. The finding that only a small portion of the customers was able to notice that the product was discounted, and was able to acknowledge how much the price was reduced, is remarkable.

Both in the studies of Conover (1986) and Dickson and Sawyer (1990) customers deviated only substantially from the exact price with their own price estimations. However, we should consider that both studies made participants assess the prices of grocery products, which means that the actual prices of these products are rather low. A consequence of this is that when a customer’s price estimation deviates 30 cents from the actual price, this might seem minimal when considering the price of a bottle of liquor, but it is a large deviation when considering the price of bread (Dickson & Sawyer, 1990). The observation that customers are not pinpoint accurate when it comes to price awareness also has other implications (K. B. Monroe, 1973). First of all, the results presented earlier suggest that most customers would be oblivious to minor price changes in the products they usually buy. In addition, they would also be unaware of price differences between two similar products. And lastly, as grocery products of the same class are usually situated within a very narrow price range, customers pay less attention to prices. In short, it appears that customers are only moderately aware of the exact prices of the products they purchase, even if these prices should catch their eye (e.g., in the case of reduced prices).

When looking at the external cues that costumers use to evaluate the price of a product, we see that the perceived quality of the product is strongly entwined with its price. Perceived quality of a product can be conceptualized as the customer’s assessment of the perceived ‘overall excellence’ of a product (Zeithaml, 1988). Although the research on the relation between price and quality yields mixed results, the general consensus seems to be that customers use price as an indicator of the quality of a product when there are no other external cues (brand name, former experience with the product) available (Dodds, Monroe, & Grewal, 1991). Interestingly, when multiple cues are available, we notice similar findings. More specifically, the meta-analysis by Monroe and Krishnan (1985) yielded that the effect of price on perceived quality is enhanced when other external cues (such as brand name) are provided. Additionally, the results of the work of Rao and Monroe (1989) suggest that the relation between price and perceived quality is stronger when multiple cues are provided, versus when only price was provided as a cue. We highlight however that these results show a trend for an enhanced relation between price and quality, but this relation was not found to be statistically significant. Although the interaction described above has been replicated several times in other work (we refer to the work of Monroe and Krishnan (1985) for a comprehensive overview), some studies (e.g., Dodds & Monroe, 1985; Render & O’Connor, 1976) found stronger effects in the single cue condition, compared to the multiple cue condition.

In addition to the influence of the provided cues, we should also consider personal differences between customers (John, Scott, & Bettman, 1986). In particular, customers may differ in the beliefs they have about the relation between price and quality. As was pointed out by the authors, customers who believed that higher prices are associated with better quality also chose products that had a higher price. Another example of a personal factor that might have an influence is the knowledge a certain customer has on the product (Lambert, 1972). It is intuitive that customers cannot use price as an informational cue if they are not aware of the regular price range for that particular product.

Another factor that might have an impact on how customers perceive the price-perceived quality relation is the type of product that is considered. To clarify, we consider two products: a jar of peanut butter and a car. When customers enter a store with the goal to buy peanut butter, they will notice that the different products they can choose from only differ substantially with respect to the price. Because of this, Dodds et al. (1991) argued that the clients use this price as a measure of 'sacrifice', and not as an indication of quality. In contrast, when someone wants to buy a new car, we can assume that the customer will use the price of the car as a reflection of quality, as the price of the car usually reflects differences in performance or included options. In line with this hypothesis, Peterson and Wilson (1985), as cited by Dodds et al. (1991), confirmed that the larger the price differences are within a product category, the more customers are willing to use price as a measure of quality. To summarize, we should take into account the beliefs customers have about the relation between price and quality, the product itself, and the buyer's knowledge on the product they want to purchase, as these factors might all play an important role in the decision-making process.

Although the concise overview provided above suggests that the influence of price on the decision-making process is well documented, we still cannot fully account for the irrational behavior customers exhibit in purchasing situations (Hinterhuber, 2015). This author argued in his work that the perceptions of both value and price can be altered without even changing them directly, suggesting that human beings are susceptible to irrational processes. When talking about 'rationality', Hinterhuber (2015) adopted the same definition as Blaise Pascal once used: behavior with the goal to maximize EV. As we have seen earlier, this notion of rationality was already disproven by the St. Petersburg paradox, but several other examples are provided that suggest that irrational behavior is also existent in a modern retail setting. Numerous fallacies are described by the author, indicating that customers are easily deceived in their judgment of prices. To illustrate this point, we shortly discuss the fallacy 'willful overpricing'. This fallacy is defined as a process where a firm sets a price higher than the initial price that one would be willing to pay. Contrary to what one might expect, this move increases the sales of the product, not only indicating that customers are irrational but also suggesting that willingness to pay is a dynamic concept that can be altered by external influences.

All fallacies described by Hinterhuber (2015) provide evidence for the irrational approach of customers when judging product offers. However, the author also argued that even the managers of the stores are not free from bias. More specifically, the managers also show irrational behavior when setting prices for their products. Again, we discuss an example to clarify what is meant with ‘irrational behavior’ in the form of another heuristic. ‘Simple heuristics’, in line with the definition provided earlier, signify that managers solve the complex problem of finding an attractive price by using simple rules-of-thumb that provide a price that seems fitting. An example of such a heuristic could be: ‘look at the other companies that are on the market, and set our price a bit lower’ (Nagle, Hogan, & Zale, 2016).

The method mentioned in the last lines of the previous paragraph is one way of determining a selling price, however, we note that only a few systematic methods for determining the best fitting price of a product have been proposed (Hinterhuber, 2004; Hinterhuber & Liozu, 2012). Hinterhuber (2004) argued in his work that there should be a focus on three dimensions when determining the best price for a product: the sources of value of this product, the impact the price has on the company profit, and the knowledge that company strategies involving pricing are of a dynamic nature. In essence, Hinterhuber's method (2004) focuses on a deep understanding of ‘customer value’, as it was argued that this is essential to be able to determine the best price.

Building on earlier research, the study of Hinterhuber and Liozu (2012) introduced three different methods that are used to determine prices: 1) ‘cost-based’ pricing, 2) ‘competition-based’ pricing, and 3) ‘costumer value-based’ pricing. The following paragraph will be used to elaborate on the available pricing techniques, and highlight their advantages and disadvantages. For an extensive overview, we refer to the original work of Hinterhuber and Liozu (2012).

‘Cost-based’ pricing determines a price based on the expenses made so far, or with the goal to get a certain amount of profit when sales start. One of the advantages of ‘cost-based’ pricing is that the data you need (e.g., the production cost) is easily accessible. However, the rivalry between different companies, and the idea that ‘price’ and ‘willingness-to-pay’ are dynamic concepts is totally neglected in this approach. This is in contrast with the second approach, ‘Competition-based’ pricing, which takes the market competition into account when determining a price. The main disadvantage associated with this approach is that a price war may be started when this method is used by a lot of companies at the same time. Finally, 'customer value-based' pricing actually focuses on the value a buyer attributes to a specific product to determine the product's selling price. So, where the other methods aim to set a high price for a product in a competitive environment, this method aims to derive a product price from what the customer wants to find in a product, and how much this new product meets the desires of potential customers. One obvious advantage is that this method allows the price to be tailored to the potential buyer. A disadvantage is that it might be hard to collect data on what a customer needs or desires. Additionally, the data collected to use in this approach also might prove difficult to interpret, making it hard to translate the results to a reasonable price.

Looking at the methods annotated by Hinterhuber and Liozu (2012), we argue that we can categorize these methods as 'explicit'. To back this statement, we should first clarify what the terms 'explicit' and 'implicit' denote for our study. We will define 'implicit' based on the definition of 'implicit memory' provided in the work of Fazio and Olson (2003). In their work, having 'implicit memory' for a certain occasion indicates that the event itself might influence your further performances, but you have no 'explicit memory' of the event itself. As the authors concisely described, the event has certainly occurred, but you are unable to explicitly recall it.

Keeping this definition in mind, we can also use it to define the terms 'explicit judgment' and 'implicit judgment'. In that regard, an 'explicit judgment' would simply signify that one makes a judgment by explicitly taking certain factors (in the context of determining a product price: 'market share', 'production price' etc.) into consideration. Alternatively, if one makes an implicit judgment, this signifies that we are more unaware of the judgment: we made it, but we are unable to explain how we came upon a certain decision. We acknowledge that the literature on 'implicit' versus 'explicit' in psychology, in general, is largely divided when it comes to providing definitions of the aforementioned terms. For the reader interested in this topic, we refer to some review studies (De Houwer, 2006; De Houwer, Teige-Mocigemba, Spruyt, & Moors, 2009), and a meta-analysis on the relation between explicit self-report measures and the Implicit Association Test (Hofmann, Gawronski, Gschwendner, Le, & Schmitt, 2005).

Going back to our main point, we argue that the explicit methods of pricing explained by Hinterhuber and Liozu (2012) are prone to certain biases (as we already highlighted in the part on heuristics). Therefore, we argue that implicit measures for defining a price might prove valuable, as these are less prone to corruption by explicit biases and heuristics.

A new approach to pricing

Because the current pricing methods rely on concepts that are hard to measure objectively (e.g., ‘customer value’, ‘market competition’), this study proposes a new customer-oriented approach to pricing. This new method relies on the work of several studies in different fields of psychology, therefore we will shortly discuss these studies in the next three paragraphs.

Our new pricing method relies partly on the hypothesis that there is a well-established link between evaluation and emotion (e.g., Strack & Deutsch, 2004). An example of such an effect was seen in the work of Chen and Bargh (1999). In this work, subjects had to move a joystick towards or away from themselves based on the valence of a presented word. The words could either have a positive connotation (e.g., ‘wonderful’), or a negative connotation (e.g., ‘disgusting’). The participants had to move a joystick corresponding with a certain emotion categorization they made about the word: half of the participants had to move the stick towards them when a positive word was presented, the other half had to move the stick towards them when they saw a negative word. The results brought forward by Chen and Bargh (1999) pointed out that participants are faster to pull positive words towards them, and to ‘push away’ negative words. The authors attributed this effect to the idea that the evaluation of a stimulus might lead to the facilitation of certain behavioral tendencies (such as pushing something negative away). For our study, we are interested both in the paradigm itself and in its implications.

As Krieglmeyer and Deutsch (2010) already formulated, these so-called ‘approach-avoidance’ tasks yield some major advantages. First of all, ‘approach-avoidance’ tasks might reveal how subjects really feel about a stimulus, even if they want to conceal their thoughts/emotions. This is in contrast with more explicit measures, such as the questionnaire, where it is easier to conceal what one really believes/thinks. Another point made by the authors is that these tasks might help to elucidate how a subject implicitly feels about a certain stimulus. Particularly, it might be used to discover stimulus evaluations that subjects are unaware of themselves. In the context of price evaluation, we might use such a paradigm to assess how subjects (implicitly) feel about a certain product-price combination. Additionally, when we encourage the participants to make their judgment as fast as possible, we would expect that there is less opportunity to rationalize their decision. In this respect, such a reaction time-based task could prove useful to reveal the implicit judgments about certain price-product combinations.

A second study that is important for our paradigm is the work of Dezwaef, Demanet, Desmet, and Brass (2018). In this study, the relation between reaction time (RT) and price judgment was investigated. More specifically, the authors measured RTs when participants were categorizing a price for specific products as ‘cheap’ or ‘expensive’. Their results indicate that participants are significantly faster to mark a price as ‘cheap’ versus ‘expensive’. It should be noted that the prices that were used were ‘extreme’ prices, where it was clear which prices associated with a certain product were far below the retail price (the price you will pay in a store), and which ones were far above. While this study shows that participants are significantly faster for cheap prices, still some questions remain unanswered. One open question is what would happen when not only ‘extreme’ price manipulations are used, but also prices that are just below, or above, the retail prices for the presented products.

Another study that proved seminal for our rational is the eminent work of Kahneman and Tversky (1979) on the ‘Prospect theory’. In this theory, the authors postulated that the evaluation of monetary change can be represented by a concave function. To give an example: the difference between gaining 50 dollars vs. gaining 100 dollars seems large. However, the difference between gaining 7000 dollars vs. gaining 7050 dollars seems less sizeable. In other words: the perception of the same monetary change differs depending on the situation. The assumption about the perception of monetary change was conceptualized by Kahneman and Tversky (1979) as follows: “the marginal value of both gains and losses generally decreases with their magnitude.” (Kahneman & Tversky, 1979, p. 278).

The results of these studies suggest that: 1) people enrolled in an ‘approach-avoidance’-inspired paradigm should be faster to stimuli that elicit stronger emotions, compared to ‘neutral’ stimuli, 2) participants should be faster for cheap prices versus expensive prices, in line with the work of Dezwaef et al. (2018), and finally 3) participants should become faster when the difference in monetary change becomes larger (i.e., the perceived price deviates more from the regular price), in line with the concave function proposed by Kahneman and Tversky (1979).

Present study

In the current study, we argue that the findings described above can be used to create a new measure of price evaluation. More specifically, we designed a paradigm in which participants had to categorize a price associated with a product as ‘cheap’ or ‘expensive’. To make sure that participants had as little time to rationalize as possible, we employed an adaptive threshold which encourages the subjects to answer as fast as possible. An advantage of a hasty price judgment is that it enables us to measure the intuitive (i.e., with minimal influence of rational thought) evaluation of the price. To investigate the difference between different response thresholds, we conducted two experiments. These experiments different only with respect to the time the participants had to categorize the prices. Additionally, we also assessed how familiar the subjects are with each product by using a questionnaire. Our hypotheses are in line with the research described above: we expect to find 1) faster RTs for prices that deviate more from the retail price, 2) faster RTs for ‘cheap’ versus ‘expensive’ prices, and 3) a concave relationship between RT and price manipulations, meaning that we expect that participants are slower for prices that are closer to the actual retail price, and faster for more extreme deviations.

Methods

Subjects

For this study, a total of 70 participants (number of females = 51, *mean age* = 21, *SD* = 2.8, range = 17-33) were recruited via the experiment sign-up site of Ghent University. These 70 subjects were split up into two groups of 35 people, one for each conducted experiment. The exploratory nature of this study prevented us from doing a power analysis prior to data acquisition. More specifically, because this study is new in its approach, we had no prior assumptions about the magnitude of the effect sizes we could expect. Therefore, we hypothesized that a sample size of 35 subjects in each group (considering we had 336 trials per subject) should be enough to conduct our statistical analyses without risking major power issues. We acknowledge that no experimental data was lost during data acquisition, while two participants failed to fill in the familiarity questionnaire. All subjects volunteered to take part in the experiment and received a course credit upon completion.

Materials

All participants were tested at the Department of Psychology of Ghent University. The participants completed the experiment on one of the test computers of the faculty of Psychology. The experiment was conducted using PsychoPy software v1.85.2 written in Python (Peirce, 2007). The stimuli that were used during the price judgment task originated from the price judgment study (Dezwaef et al., 2018) that was briefly reviewed in the introduction.

Procedure

At the start of the experiment, we first made sure that the participants were oblivious to the purpose of this study, and that they had never participated in an experiment that used a similar procedure. The subjects learned that the experiment comprised of two different phases: first, they were asked to complete a price judgment task, and then they were asked to fill in an online familiarity questionnaire. All subjects were informed that they should answer intuitively during the price judgment task, implying that they should not overthink their answer too much. All participants signed the informed consent, and afterward, the participants were debriefed and thanked for their participation.

We note that two experiments were conducted, however, these experiments only differ with respect to the response threshold. Therefore, we will first elaborate on the general procedure which was identical across the experiments, and we will come back later in this section to the differences in response threshold between Experiment 1 and Experiment 2.

Price judgment task. In this task, the participants are informed that they should respond as fast as possible to a price that is shown on screen. Before the price is displayed, however, a specific product (e.g., a can of tic tac sweets) is displayed shortly. The participants are instructed to respond as fast as possible to the displayed price shown immediately after. With this response, they should indicate whether they believe the displayed price is a low or a high price for the product that was shown immediately prior to this price. In total, seven different price manipulations (-70%, -40%, -10%, regular price found in the supermarket, +10%, +40% and +70%) are shown with each product. During the experiment, eight different products are shown. All products are grocery products that proved well-known to the general population (Table 1 provides a description of all displayed products, along with their regular price).

The trial starts with a fixation cross that is displayed for 500 milliseconds, followed by the presentation of the product, which remains on screen for 2500 milliseconds. Subsequently, the price is displayed. The participants should react as fast as possible to this price, indicating in the process whether they regard this price as low or high. An overview of a possible trial in the experiment can be seen in Figure 1.

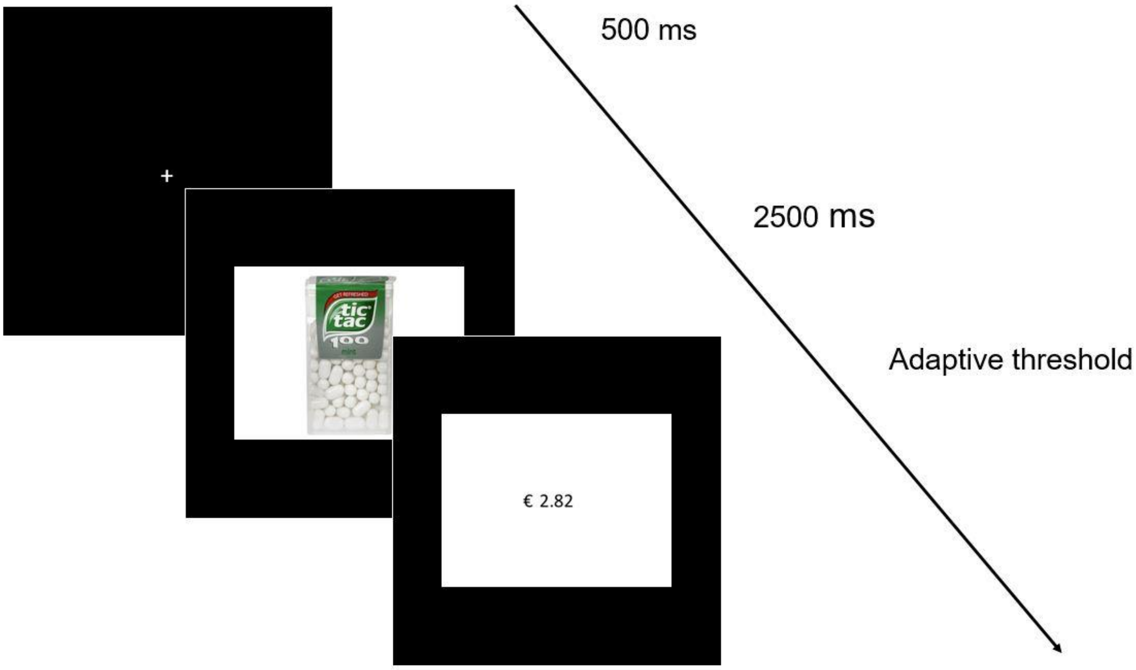

Figure 1. depiction of the first trial subject 1 saw. In this specific trial, the participant had to indicate whether 2 euros and 82 cents is 'cheap' or 'expensive' for a can of tic tac sweets. Next to the arrow we outline the amount of time the subject saw each phase of this trial.

Note that the amount of time the price is displayed is variable: the time the participants had to respond to the price depended on an adaptive response threshold (ARD). Later in this method section, we will elaborate on how this ARD was calculated. If the participants answered within the allowed time window, the computer would start with the next trial. However, if they were too slow, they would see a message stating that they were too slow, and they were encouraged to answer faster next time. By using this ARD, the participants were stimulated to answer as fast as possible, reducing the chances that they used rational thought to evaluate the prices they saw.

To indicate whether they think a price is 'low' or 'high', the participants used two marked buttons on the keyboard of their experiment computer. They used both their left (for cheap prices) and right (for expensive prices) index fingers to manipulate these buttons.

Randomization. During the experiment, eight different products are shown to the participants. Each product has a regular price (the price paid in the store to obtain the product). For our experiment, six derivations of this regular price were computed. So, at the end of this process, we had seven different prices (regular plus the six derivations) that could be linked to a certain product. In each trial, a product and a price are shown together (following the procedure displayed in Figure 1). Thus, the participants see 56 (seven times eight) unique price-product combinations. In the experiment itself, the participants completed six blocks of these 56 unique combinations. Thus, the entire experiment consisted of a total of 336 trials. To explain the randomization used, we refer to table 1, which represents the first 16 trials that participant 1 encountered. We first note that we made sure that every possible product-price manipulation combination was created, yielding a total of 56 combinations. Subsequently, we grouped the data into smaller blocks of 8 combinations, where each product appeared once in this smaller block. This refers to the first eight trials in table 1.

Table 1

Depiction of the first 16 trials subject 1 saw

First 16 trials for participant 1

Trialnumber	Product shown	Brand	Regular price	Price manipulation	Shown price
1	product3	tic tac	€ 2.00	+40%	€ 2.82
2	product6	Lays	€ 1.42	+10%	€ 1.56
3	product7	Herta	€ 3.74	-10%	€ 3.34
4	product5	Minute Maid	€ 1.24	+70%	€ 2.11
5	product2	Coca-Cola	€ 1.71	-40%	€ 1.06
6	product8	Haribo	€ 3.48	-70%	€ 1.01
7	product1	Lipton	€ 2.31	-70%	€ 0.72
8	product4	Philadelphia	€ 2.53	0%	€ 2.53
9	product3	tic tac	€ 2.00	-40%	€ 1.18
10	product5	Minute Maid	€ 1.24	0%	€ 1.24
11	product4	Philadelphia	€ 2.53	+40%	€ 3.57
12	product6	Lays	€ 1.42	+70%	€ 2.42
13	product1	Lipton	€ 2.31	-10%	€ 2.08
14	product8	Haribo	€ 3.48	-10%	€ 3.12
15	product2	Coca-Cola	€ 1.71	-70%	€ 0.54
16	product7	Herta	€ 3.74	+10%	€ 4.11

We note that some price manipulations occur multiple times within the same block of eight trials, be it with different products. However, we ensured that the entirety of 56 combinations was balanced. We created six blocks of 56 trials that followed this same structure. The randomization was done prior to the data acquisition, so the trial order was already predetermined for every participant separately.

Adaptive response deadline. Because this experiment heavily relies on RT ratings, an adaptive response deadline (ARD) is imposed. More specifically, this ARD ensures that the time the participants get to express their evaluation of the price is tailored to their individual response times. The ARD makes sure that the time the participants have to answer is based on their mean RT in the last smaller block of eight trials (as defined above) they completed. As we mentioned earlier, the ARD is different for the two experiments. In Experiment 1, the ARD of a current block of eight trials equals the mean RT of the last completed block of eight trials. On the other hand, in Experiment 2, we compute the mean RT of the last block of eight trials, and additionally add 1.5 times the variance of all RT measures to the mean.

To explain the difference more clearly, we assume that a participant has an average RT of 800 milliseconds in the first eight trials, and an RT standard deviation (SD) of 200. In Experiment 1, this means that the participant will have 800 ms to respond to the next eight trials in the experiment. Here, the standard deviation is left unused. In Experiment 2 on the other hand, the ARD for the next eight trials will equal 1100 ms, as 1100 = 800 + 1.5 * 200. When the participant is too slow, feedback is provided. The ARD is different for each block of eight trials, and always uses the mean RT of the past smaller block. The used SD corresponds to the SD of the RTs across all trials for that specific subject. Using this approach, we control how much time the participants have to react to trials based on their natural RT.

In the very first block of eight trials, there is no response deadline, as we have no idea of the natural RT of the participants at that moment in the experiment. This first block is an exercise block, which is used to define the ARD of the next eight trials. Additionally, it also makes the participants comfortable with the procedure of the experiment. The trials in which they reacted too slowly are also saved for later analysis. In its entirety, the price judgment phase lasts around 25 minutes.

Questionnaire. The participants additionally filled in a computer-based questionnaire upon completing the price judgment task. Particularly, the participants indicated whether they recently bought the products they saw during the experiment. For each product, they could answer using a 5-point Likert scale, with options ranging from ‘Yes, I buy this product very often (every week)’ to ‘No, I have never bought this product’. All questions in this online questionnaire were asked in Dutch. For a visualization, we refer to Figure 2 immediately below.

Figure 2. how often does one buy the product?

Results

General information

All data analyses described below were performed using RStudio (R Core Team, 2016). In all our analyses, we used a linear mixed-effects approach, using the R package 'lme4' (Bates, Mächler, Bolker, & Walker, 2015). We created two different models for each experiment to test the hypotheses described at the end of the introduction: one model contains 'price' as a categorical predictor, while the other model incorporates 'price' as a standardized continuous predictor. In both cases, the dependent variable is RT (in milliseconds). The categorical model was created to gain insights into the fluctuations in RT associated with each level of price manipulation. In other words: this model allowed us to see how RT changed, for example, for the '-70%'-condition, displaying the increase or drop in RT associated with this price level. On the other hand, we also needed a model with a numerical predictor to test the inverse U-shape hypothesis: we had to square 'price' as a predictor, and this can only be done when price is a continuous predictor. Hence, we created two different types of models for our analyses.

Experiment 1

As mentioned above, we selected RT (M = 536 ms, SD = 218, range = 202-3323) as the dependent variable in our model. As a fixed effect, we included 'price' (M = 2.31 euro, SD = 1.37, range = 0.37-6.36), in line with our hypothesis that 'price' has a systematic effect on the RT. It should be stressed that, in the analysis described below, price was treated as a categorical variable. This categorical variable consisted of seven levels (the seven price manipulations). As the reference level, we opted for the level '+0%'. This because this level corresponded with the actual retail price for each product. As random effects, we included 1) 'subject', controlling for the individual differences with respect to RT, and 2) 'product', acknowledging that different products might elicit different RTs. This specific model was selected after model comparison using the RStudio function 'anova()'. The R^2 statistic of this model was computed using the R library 'MuMIn' (Barton, 2018), which returns a statistic describing the percentage of variance explained both by the fixed-, and random factors included in the model; $R^2 = 0.37$.

Before explaining our created models any further, we would first like to summarize some other results extracted from the data. Prior to the analysis, we first rejected trials based on the reaction times of the participants. First, all trials with an RT below 200 ms, and an RT above the mean RT of the participant plus three times the SD of their RT were excluded from further analysis. In Experiment 1, this meant that a total of 196 trials were rejected, which corresponds to 1.70% of the entire dataset being deleted.

Additionally, we also looked at how many times the participants were 'too slow', meaning that they answered slower than the ARD. In Experiment 1, we noted that the participants were 'too slow' in 18.87% of the trials in total. Looking at these results, we remark that the ARD in this experiment might have been too tight. We will return to this point later on. In the next paragraph, we will focus on the use of linear mixed-effects models to determine how RT might differ for different levels of 'price'.

Our analysis pointed out that there was a significant effect of price ($F(6, 35) = 8.5$, $p < 0.001$). Looking more in depth at the fixed effect, we see that three levels of 'price' prove significant: 1) the '-70%'-level, $\beta = -34.83$, $SE = 6.05$, $p < 0.001$, 2) the '+40%'-level, $\beta = -11.94$, $SE = 6.06$, $p = 0.05$, and finally 3) the '+70%'-level, $\beta = -21.26$, $SE = 6.06$, $p < 0.001$. Thus, this analysis implies that the more extreme prices have a significant impact on RT, where participants react significantly faster (deduced from the negative sign of the beta values) for prices further away from the reference price. Furthermore, we would like to note that the other coefficient estimates were also negative, indicating that participants are faster when they see a price that deviates from the reference price. We stress however that these estimates were non-significant.

In the second part of the analysis of our first experiment, we included price as a continuous predictor. To test whether an inverse U-shaped relationship can be observed between the observed price and RT, we first created a new predictor by standardizing the numeric prices seen during the experiment (from here on referred to as 'standardized price'). Additionally, we added another variable by squaring 'standardized price', and inverting its sign. In other words, we created two variables, x and $-x^2$, to see which predictor is better. Then, we compared these two models: the one with only standardized price as a predictor of RT, and the other model that incorporated both standardized price and the inverse square of the price as predictors. While these variables functioned as fixed effects, we also added 'subject' and 'product' as random effects in both models. The results of this model comparison yielded that the inverse square model came forward as the best model ($\chi^2(1) = 71.90$, $p < 0.001$). Looking more closely at the 'winning' model, we see that standardized price, $t(3.45)$, $p < 0.001$, and the inverse square standardized price are both significant, $t(8.54)$, $p < 0.001$. This analysis implies that an inverse squared predictor is better in accounting for the observed RTs than a linear predictor.

We also hypothesized that there is a difference between the highest prices and lowest prices in terms of RTs, where we expect participants to be faster for cheaper prices. To test this hypothesis, we conducted a one-sided paired t-test to compare the mean RTs for '-70%' (the cheapest price) and '+70%' (the most expensive price) for the participants of Experiment 1. The results yielded from this analysis indicate that there is a marginally significant difference in mean RT between the cheapest price ($M = 512$, $SD = 191$) and the most expensive price ($M = 527$, $SD = 207$); $t(34) = -1.58$, $p = 0.06$. This indicated that RTs were significantly lower for the cheapest price.

Finally, our last hypothesis was that the relationship between RT and price could be conceptualized as an inverse U-shape. We refer to Figure 3, where we plotted the coefficient estimates for our categorical model of price. We will briefly explain what the points in Figure 3 mean. The point at '0% (reference)' is our reference level. The value there represents the predicted value for the dependent variable (i.e., reaction time) when all the independent variables are zero. Keeping in mind that our only independent variable (i.e., price category) is a categorical variable, the interpretation of the estimates depends on the chosen reference level (thus, in this case, the '0%'-price level).

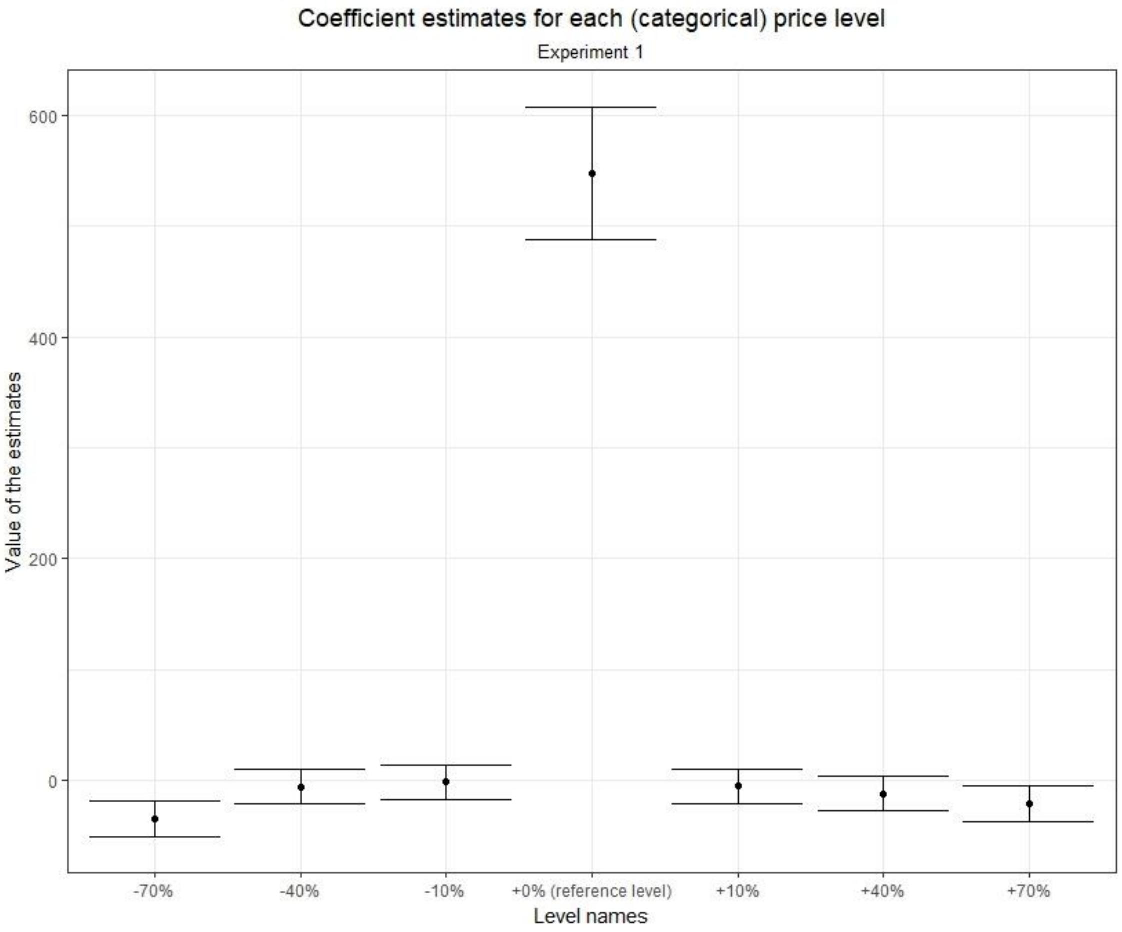

Figure 3. estimated coefficients yielded by the categorical model in Experiment 1. We see that all the estimates for the price deviations are negative.

Looking at the other estimates, we visually see that the estimates are all negative, with a 95% confidence interval (CI) that includes zero in four out of six times. The only exceptions are the '-70%'-price level, and the '+70%'-price level. We remark that in our analysis the '+40%'-price level also proved significant. However, the p-value associated with this was 0.05. As Figure 3 works with a 95% CI, it can be noted that the CI of the '+40%'-level estimate also appears to include zero. Nonetheless, this plot reinforces our analyses by suggesting that the two most deviating price levels are significant. Importantly, this plot also suggests that the relation between price-level and impact of RT is inverse U-shaped, where more extreme price levels have a larger impact on RT. Although our analyses with both price as a categorical-, and a continuous predictor already suggested that the inverse U-shape is present, this plot further reinforces our hypothesis.

Summarizing the results of Experiment 1, we note that we have found evidence pointing in the direction of one hypothesis described in the introduction: participants become faster for more extreme prices, an effect that is present for both the cheaper and more expensive prices. However, we found only a marginally significant difference between the cheapest and most expensive price manipulations in terms of mean RTs across subjects. Additionally, our plotting efforts also suggest an inverse U-shaped relationship between RT and the amount of deviation from the reference price.

We noted earlier that participants were too late to pass their judgment in almost 20% of the trials. We argued that this might be too much and that this might indicate that our ARD was too tight. In other words: the reaction times measurements might be too heavily impacted by this ARD (leading to less variation in the data). Therefore, we conducted another experiment, where the ARD was more forgiving.

Experiment 2

As was noted earlier, the second experiment allowed more time for the participant to press the desired response button before they were encouraged to respond faster. Similar to the analysis of the data of Experiment 1, we focused on RT in milliseconds (*M* = 704 ms, *SD* = 295, range = 234-3775). Again, we included 'price' (*M* = 2.31 euro, *SD* = 1.37, range = 0.37-6.36) as a fixed effect in different models: once with price as a categorical predictor (with '+0%' as reference), and once as a standardized continuous predictor. As random effects, we included 'subject' and 'product', this for the same reasons explained in Experiment 1. The R^2 statistic was computed using the same procedure described above (Barton, 2018); $R^2 = 0.39$. Similar to the computation above, this value represents that 39% of the variance in the model can be explained by the included fixed-, and random effects. Before we dive any further into the analysis, we will first briefly describe some behavioral data.

Similar to the procedure in Experiment 1, we first rejected trials based on the reaction times of the participants. The same criteria as before were used in our data cleaning. Our results were similar to Experiment 1, with 176 trials being rejected. This corresponds to 1.49% of the data being lost.

We also looked at how many times the participants were 'too slow'. In

Experiment 2, we see that the participants were 'too slow' in 3.60% of the trials in total. Thus, it seems that the change in ARD-definition did have an effect on our results. Now, we will focus on the main analysis, where we first elaborate on a model with 'price' as a categorical predictor.

Our analysis of the data of Experiment 2 shows results similar to the results of Experiment 1: a significant effect of price on RT was observed ($F(6, 35) = 69.08$, $p < 0.001$). When we disentangle the contribution of the different price levels, we note that several levels prove significant: '-70%' ($\beta = -116.34$, $SE = 8.03$, $p < 0.001$), '-40%' ($\beta = -35.97$, $SE = 8.06$, $p < 0.001$) '+40%' ($\beta = -57.98$, $SE = 8.06$, $p < 0.001$) and '+70%' ($\beta = -98.24$, $SE = 8.05$, $p < 0.001$). The results of this analysis put forward the notion that RT is influenced by the price level, indicating that more extreme prices (such as '-70%' and '+70%') have a facilitating impact (looking at the sign of the estimates) on RT. Thus, the more extreme the price, the more the RT appears to drop. Looking at the non-significant levels ('-10%' and '+10%'), we remark that the estimates associated with these levels are also negative, indicating that subjects react faster to a price that deviates from the reference price. Again, we highlight that subjects did not react significantly faster to these smaller deviations from the reference.

Now centering our attention on price as a continuous predictor, we once more aimed to test whether there is an inverse U-shaped relationship between price and RT. Following the same procedure as described above, we created two new predictors: the standardized price, and – (standardized price)². We created two different models with these two variables as fixed effects, and 'subject' and 'product' as random effects. Model comparison pointed out that the relationship between price and RT is explained better by a model with both the standardized price and an inverse squared price as predictors; ($\chi^2(1) = 306.68$, $p < 0.001$). Thus, this analysis suggests once more the relation between RT and price is explained better by an inverse quadratic relation.

To see whether participants are faster for cheap prices compared to more expensive prices, we again conducted a one-sided paired t-test to compare the mean RTs for '-70%' ($M = 635$, $SD = 216$) versus '+70%' ($M = 654$, $SD = 230$) across subjects. In this case, we found a significant difference between the mean RTs; $t(34) = -1.86$, $p = 0.03$. Again, this is indicative of the idea that participants react faster for the cheapest prices, compared to the most expensive ones. These findings are similar to the results of Experiment 1.

Visualizing the relationship between price and RT, we observe an inverse U-shape (please see Figure 4). Similar to Figure 3, we note that '+0%' is taken into account as the reference level, and the other estimates represent the deviations with respect to the RT for each price level. We again note that more extreme deviations have more impact on RT. We additionally note that we can visually see that more estimates, and their accompanying 95% CIs, are below zero, indicating that RT significantly drops for these levels. This plot again suggests an inverse U-shaped relationship between RT and the price deviations. Additionally, we remark that the estimate for the reference level is larger as compared to Experiment 1. We hypothesize that this is attributable to the different ARD used in Experiment 2.

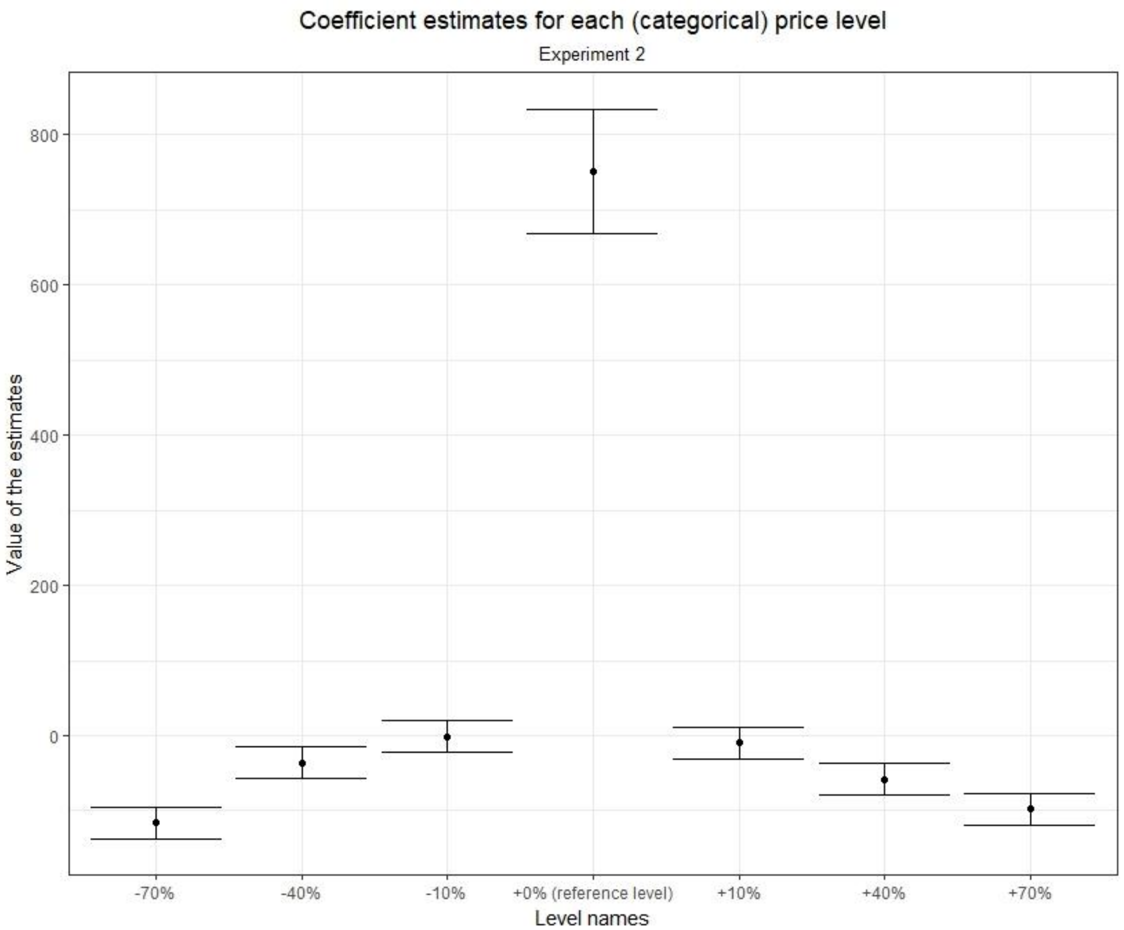

Figure 4. estimated coefficients yielded by the categorical model in experiment 2. We see that the estimates are negative for the price deviations.

Outlining the results of the analysis for Experiment 2, we remark that we have evidence for our hypotheses: participants react faster for prices that deviate more from the reference price, and participants are significantly faster for the cheapest price compared to the most expensive price. Additionally, the relationship between RT and price level appears to be of an inverse U-shaped nature, where the relation is more pronounced than in Experiment 1.

Familiarity

In this final part, we will briefly look at how familiar our subjects were with each product presented during this study. Because there were no hypotheses concerning the impact of familiarity on RT, we only did an exploratory analysis. In Table 2, we displayed the percentage of participants (of a total of 68 participants) that choose a specific option in the familiarity questionnaire for each product.

Table 2

Familiarity ratings (in percentages chosen)

Familiarity ratings for each product across experiments

Brand	Never bought	Bought once	Less than monthly	Monthly	Weekly
tic tac	32,35	54,41	11,76	1,47	0,00
Lays	11,76	17,65	33,82	26,47	10,29
Herta	44,12	16,18	25,00	13,24	1,47
Minute Maid	23,53	41,18	22,06	7,35	5,88
Coca-Cola	17,65	32,35	22,06	19,12	8,82
Haribo	36,76	39,71	20,59	1,47	1,47
Lipton	14,71	45,59	25,00	14,71	0,00
Philadelphia	51,47	23,53	17,65	7,35	0,00

Looking at these results we see that some products have a high percentage for 'Never bought' (e.g., Philadelphia with more than 50%). On the other side of the spectrum, we see that only a few products are bought weekly. If this occurred, it was always for a small subgroup of our subject group (e.g., 'Lays' was bought weekly by 10% of the 68 participants). This might suggest that most of our subjects were not that familiar with the displayed products. In conclusion, we note that some products might be replaced when we select our participants from a student subject pool, such as

‘Philadelphia’ and ‘Herta’. This because these products score rather high on the ‘Never bought’-item of our questionnaire.

Discussion

The aim of this study was to investigate whether RT measures could be used to implicitly measure a participant’s affinity for a certain price for a retail product. To explore this research question, we conducted a computer experiment where participants briefly saw a product, instantaneously followed by a price. Immediately after, the participants were asked to indicate whether they perceived the price as ‘cheap’ or ‘expensive’ for the product they last saw. They passed their judgment using two response buttons. Critically, the participants were forced to make a quick assessment, as a response deadline was imposed during the price evaluations. This response deadline was installed to ensure that the judgment was made without overthinking the decision, attempting to measure an ‘automatic’ judgment of the price. In two separate experiments, we measured the RTs associated with the price judgment. It should be stressed that the response deadline in Experiment 1 was more strict than the imposed deadline in Experiment 2. Because our results indicated that participants were ‘too late’ in about 20% of the trials in Experiment 1, we decided to conduct Experiment 2 which incorporated a more forgiving response threshold. We hypothesized that 1) participants react faster to prices that deviate more from the actual retail price, 2) participants react faster to cheap prices, as opposed to more expensive prices, and 3) the relationship between price and RT exhibits an inverse U-shape.

Our results suggest that participants are faster for prices that deviate from the reference prices, both for cheaper and more expensive prices. This was found in both Experiments 1 and 2, and observed both when ‘price’ is included in our analyses as a categorical predictor, and a standardized continuous predictor. Additionally, we found that participants are significantly faster for the cheapest price, as compared to the most expensive price. However, this was only found in Experiment 2, while in Experiment 1 this effect proved only marginally significant. Finally, the idea that the relationship between price and RT is inverse U-shaped is bolstered by the visualization of our collected data.

Generally speaking, the outcome of this study seems promising, as it seems the case that participants react faster to prices that deviate from the reference price. To explain why this is the case, we refer to the work on approach-avoidance paradigm, already briefly mentioned in the introduction. Some of the authors in this field (e.g., Chen & Bargh, 1999; Lang & Bradley, 2008) suggest that emotion serves as a preparation for a certain action. More specifically, a certain emotion might help the participant to react accordingly to a certain emotionally salient stimulus.

We might explain our own results using this framework: faster RTs for extreme prices might occur because these prices elicited a specific emotion, which prepares the participant for pressing a certain response button. In other words: the emotion associated with seeing a very low price might serve as a preparatory cue for pressing the 'cheap' button. The stronger the elicited emotion, the more the participants would be prepared to press the button.

When it comes to implementing these results in a real-life pricing approach, we hypothesize that the product price should be selected where the participants react the slowest. Following the approach-avoidance rationale, this would suggest that the participants do not have an immediate implicit judgment for that specific price. In other words, they do not immediately categorize the price as 'cheap' or 'expensive'. By using this paradigm, one might be able to set a price without having to fear for prices that are way too high or too low, as this might be picked up by our implicit price judgment method.

Our results also point out that participants are significantly faster for the most extreme price levels, this both in Experiment 1 and 2, while no significant results are found for the price levels closer to the reference price. Additionally, we also see an inverse U-shaped relationship between the standardized prices and the mean RTs associated with these prices. We can account for both findings using the famous 'Prospect theory' (Kahneman & Tversky, 1979). This theory, as explained earlier, states that the impact of monetary change depends on the relative impact it has on one's finances, not the absolute impact. Consequently, the larger impact of prices further away from the reference price seems to be in line with the Prospect theory. Additionally, the idea of a concave function (inverse U-shape) was also postulated by Kahneman and Tversky, which may also account for the shape of the relationship between standardized price and mean RT we found back in our own data. This shape is in line with the idea that more extreme prices have more impact.

The hypothesis that people would be faster to react to low prices came from other research that suggested that participants are faster to process positive information. To exemplify this, we refer to the work of Unkelbach et al. (2010), where it was shown that participants react faster to positive words versus negative words. Additionally, it was illustrated by the work of Leppänen, Tenhunen, and Hietanen (2003) that participants react faster to positive faces versus negative faces, a response which was attributed to premotoric processes. In other words, these studies suggested that human beings are faster to process positive material. We can relate their findings to our own results by hypothesizing that prices that are very low are perceived as positive, while very high prices are perceived as negative. Assuming that this is the case, we would also postulate that participants are faster for the cheap prices, compared to the expensive ones. It should be noted that we are not certain that participants view low prices as 'positive', as we did not collect any data on this. In our conducted experiments, we found some evidence for this hypothesis: in Experiment 1, the difference in mean RT between the most extreme price levels proved marginally significant, while the difference was significant in Experiment 2. We speculate the difference is not significant in Experiment 1 because of the strict response deadline that was imposed here: because the participants had very little room to answer, the RTs did not have much room to differ. It could be that because of this the interaction proved only marginally significant.

Further research opportunities

One of the most challenging endeavors might be to validate the method proposed in this research paper. While our research suggests that RT measurements might be of use in the pricing practice, we first need to validate our method on a larger sample size, and with more products before we can implement it in practice. One way to do this might be to measure customers their willingness-to-pay (WTP). In other words, one can attempt to assess how much someone wants to maximally pay for a certain product. Then, we can compare the prices yielded by the WTP procedures with the prices obtained via the implicit method illustrated in this paper. In this regard, we would expect that the prices yielded by the WTP should also be the prices where subjects are at their slowest for marking the price as ‘cheap’ or ‘expensive’. By validating this method, we can assess the value of this new paradigm for setting the prices of individual products.

In line with the need for validation, another idea for further research could be to look at more expensive prices. In our current design, we looked at various products that can be bought in a supermarket. While these products should approximate the purchases an average customer makes when shopping in a supermarket, it could be interesting to look at more expensive products such as televisions, computers, smartphones or other products that have a price far above 500 euro. A new study that incorporates both ‘normal priced’ products and ‘expensive’ products could tackle this issue.

Limitations of this study

We acknowledge that our R^2 of the models we created is not high: only 37% and 39% of the variance is explained by the fixed -, and random factors in the models of Experiment 1 and 2 respectively. However, we stress that these R^2 measurements were computed for linear mixed-effects models, so the interpretation of this R^2 is not straightforward. To make up for this, additional data should be collected to see which predictors are useful for predicting RT when participants are evaluating prices. An example of a possible predictor could be ‘desire to buy’ the specific product.

Conclusion

We showed that the magnitude of the price influences how fast subjects are to categorize the price as ‘cheap’ or ‘expensive’. This result suggests that RT might be used as an implicit measure of price evaluation. The next steps for this method are its validation, and further exploration of its uses with different product types (e.g., focusing on different price ranges). While our results pave the way for more research focusing on implicit price judgments, we acknowledge that other research is necessary to elucidate how human beings evaluate prices.

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