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The neural bases of price estimation: Effects of size and precision of the estimate

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ABSTRACT

People are often confronted with the need of estimating the market price of goods. An important question is how people estimate prices, given the variability of products and prices available. Using event-related fMRI, we investigated how numerical processing modulates the neural bases of retail price estimation by focusing on two numerical dimensions: the size and precision of the estimates. Participants were presented with several product labels and made market price estimates for those products. Measures of product buying frequency and market price variability were also collected. The estimation of higher prices required longer response times, was associated with greater variation in responses across participants, and correlated with increasing medial and lateral prefrontal cortex (PFC) activity. Moreover, price estimates followed Weber's law, a hallmark feature of numerical processing. Increasing accuracy in price estimation, indexed by decreasing Weber fraction, engaged the intraparietal sulcus (IPS), a critical region in numerical processing. Our findings provide evidence for distinguishable neural mechanisms associated with the size and the precision of price estimates.

1. Introduction

We regularly need to estimate prices, whether to decide if a product has a fair value, to plan a budget or to make a bid. An intriguing question is how people estimate the market price of a good, given the variability of products and prices available. A buyer's judgment of an item's price is an important determinant of whether or not to purchase (Thomas & Morwitz, 2009). Hence, unravelling the neurocognitive underpinnings of our intuition for prices may advance knowledge on price cognition and its implications to everyday purchasing decisions.

Behavioural research has shown that given a product name, people can quickly provide a market price in a familiar currency. As proposed by Dehaene and Marques in their studies of price estimation, people's judgment of the market value of goods depends, at least in part, on numerical processing, i.e., our mental representation of magnitudes (Dehaene & Marques, 2002; Marques & Dehaene, 2004). Indeed, prices are a good example of a numerical property of products. Like other numerosities, prices are subject to two critical effects: the distance effect, i.e., the comparison between two prices is slower and more error prone when the prices are closer than further apart; and the size effect, i.e., comparison difficulty increases with increasing price (Cao, Li, Zhang, Wang, & Li, 2012; Dehaene & Marques, 2002; Moyer & Landauer, 1967). These effects reveal that the representation of quantities is approximate, rather than exact, and that larger quantities are increasingly less discriminable.

Previous studies have shown that price knowledge obeys Weber's law. The law states that the ability to psychologically discriminate numerical values depends on the ratio between the values being compared, rather than their absolute difference (e.g., adding 5 grams to 100 grams or adding 10 grams to 200 grams has the same perceived increase on weight, as the ratio is the same in both cases). Weber's law adequately predicts performance on numerical tasks (see Cantlon, Platt, & Brannon, 2009 for a review), including price judgment tasks (Webb, 1961). For example, Lambert (1978) reported that the frequency with which participants noticed a change in the price of a product did not depend on the absolute price change, but on its ratio to the item's price. Dehaene and Marques (2002) have shown that, when participants were asked to estimate prices for different items, the standard deviation of price estimates across participants was directly proportional to the mean price, such that the higher the price the larger the variability of the estimates. Importantly, it has been demonstrated that the ratio of the standard deviation to the mean, broadly known as Weber fraction, is stable across different price magnitudes (Dehaene & Marques, 2002). The Weber fraction is thus considered an index of an item's price estimation precision, with higher values indicating a "noisier" and less precise estimation of the item's price (Whalen, Gallistel, & Gelman,

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1999). As such, the Weber fraction for a given product, calculated across participants, may be used as a proxy for the accuracy of the numerical representation of that product's price.

At a neural level, there is extensive evidence that the brain has specialized networks to process numerical quantities, notably in the intraparietal sulcus (IPS) and surrounding parietal regions (e.g., Butterworth, 2010; Cantlon et al., 2009; Cantlon, 2012; Cohen Kadosh, Cohen Kadosh, Kass, Henik, & Goebel, 2007; Dehaene, Piazza, Pinel, & Cohen, 2003; Dehaene, 2009; Emerson & Cantlon, 2014; Nieder & Dehaene, 2009; Nieder & Miller, 2004; Piazza, Izard, Pinel, Le Bihan, & Dehaene, 2004; Piazza, Pinel, Le Bihan, & Dehaene, 2007; Pinel, Piazza, Le Bihan, & Dehaene, 2004; Rivera, Reiss, Eckert, & Menon, 2005). Considered the core magnitude system, the IPS is systematically activated when quantity is manipulated, independently of notation (Piazza, Mechelli, Price, & Butterworth, 2006; Pinel, Dehaene, Riviere, & Bihan, 2001), and for various tasks, including mental arithmetic (Klein, Nuerk, Wood, Knops, & Willmes, 2009; Venkatraman, Ansari, & Chee, 2005), number comparison (Ansari, Fugelsang, Dhital, & Venkatraman, 2006), and digit detection (Eger, Sterzer, Russ, Giraud, & Kleinschmidt, 2003). The reliable activation of the IPS and neighbouring superior and inferior parietal lobules has been confirmed by various meta-analyses targeting number processing in humans (Arsalidou & Taylor, 2011; Sokolowski, Fias, Bosah Ononye, & Ansari, 2017; Sokolowski, Fias, Mousa, & Ansari, 2017). Interestingly, neuroimaging data have shown a weberian neural response in bilateral IPS. In an fMRI adaptation study, participants repeatedly viewed the adaptation stimuli (sets with a fixed number of dots), while deviant stimuli (sets of variable number of dots, along a continuum, spanning from half to double the adaptation values) were presented rarely. As predicted by Weber's law, IPS activation for deviant numerical stimuli was a direct function of the ratio between the deviant and the adaptation number (Piazza et al., 2004). Given its role in processing other numerical quantities, it is predictable that IPS also sustains our ability to estimate the market price of goods.

In the present fMRI study, we investigated the neurofunctional correlates of market price estimation, focusing on two numerical dimensions: the size and precision of the estimates. In line with previous research that shows that larger magnitudes are represented in a fuzzier, less exact manner (as evidenced by the size effect), we expect that higher prices will be more difficult to estimate, as participants must indicate a specific price within a range of values that are less discriminable than lower prices. Moreover, the computation of prices may also be influenced by factors that are extrinsic to numerical dimensions. Among these, buying frequency and market price variability have been shown to have an impact on market price estimation (Dehaene & Marques, 2002; Giuliani, D'Anselmo, Tommasi, Brancucci & Pietroni, 2017; Marques & Dehaene, 2004). Specifically, it is harder to estimate the price of products that are less frequently purchased as well as prices with greater variation in the marketplace, as revealed by longer response times (RTs) and greater variability across participants' responses. Importantly, both buying frequency and market price variability are strongly related with price magnitude, since products with higher prices tend to have lower buying frequency and greater market price variability. As such, both the approximate nature of numerical processing (with increasingly "noisier" representations as the values get larger) and purchasing factors (notably, buying frequency and market price variability) may increase the processing demands associated with the estimation of higher prices. Greater cognitive control may be necessary in order to select a specific price among a range of subjectively closer values and to manipulate multiple price representations associated with greater market price variability. Areas engaged in cognitive control, notably lateral and medial prefrontal cortex (PFC; Ansari et al., 2006; Emerson & Cantlon, 2014; Rivera et al., 2005) would be expected to demonstrate a positive correlation with increasing price estimates. Thus, it is of interest to investigate price estimation effects in regions outside the IPS.

Regarding the precision of the estimates, following previous studies, we will use the Weber fraction as an index of the price estimation accuracy. We hypothesize that a more precise representation of the price, indexed by a smaller Weber fraction, will engage the IPS, the neural signature of the mental representation of numbers.

Table 1
Descriptive statistics of the items' rating judgments and price estimation measures obtained in the behavioural study.

	Mean (SD)	Range
Rating judgments (7-point scales)		
Familiarity	5.36 (1.26)	2.57–6.89
Imageability	6.33 (0.67)	3.50–6.86
Subjective liking	4.86 (1.05)	2.18–6.86
Market price variability	3.35 (1.26)	1.29–6.36
Buying frequency	3.26 (1.18)	1.04–5.32
Price estimation measures		
Price estimates (in €)	25.87 (81.66)	0.13–530
Weber fraction	0.49 (0.21)	0.15–1.23
RT (in ms)	4185 (629)	3217–6286

2. Method

2.1. Participants

Twenty healthy participants (17 females, $M = 19.65$ years, range: 19–29 years) took part in the study. All were right-handed, native speakers of Portuguese, and had no history of neurological impairment or head injury. They all gave informed written consent to the experimental procedure, which was approved by the local ethics committee. All participants were university students and received a course credit as compensation for their participation.

2.2. Materials

Sixty-four everyday items were selected from a database of previous studies (Dehaene & Marques, 2002; Marques & Dehaene, 2004). Items denoted a broad range of products including groceries (e.g., biscuit pack), toys (e.g., video game), apparel (e.g., sport shoes), household items (e.g., light bulb), entertainment (e.g., movie ticket), electronics (e.g., laptop computer), and transportation (e.g., bus ticket). Product labels were made up of two words, presented in the written form, and no number words were used.

The features of these items and their impact in the price estimation task were evaluated in a separate behavioural study. In this study, a group of 28 participants (16 females, $M = 23.96$ years, range: 18–35 years), who did not take part in the fMRI study, provided their market price judgments of each product, by typing the estimated price on the keyboard. RTs were measured from the onset of the product presentation to the onset of typing a response. After the price estimation task, participants rated on a 7-point scale each item on several dimensions including familiarity (1 = very unfamiliar to 7 = very familiar), imageability (1 = very low imageability to 7 = very high imageability), subjective liking (1 = do not like 7 = like very much), market price variability (1 = very low market price variability to 7 = very high market price variability) and their own buying frequency of the product (1 = rarely ever buy to 7 = buy very often). As it can be seen in Table 1, the selected products presented relatively high levels of familiarity (i.e., participants reported knowing the items, with no product being rated as unfamiliar) and imageability (i.e., people reported being able to imagine the product from the labels provided). For the other dimensions, the full range of the scale was used, with items varying in subjective liking, market price variability and buying frequency.

Correlation analyses between these dimensions and the log transformation of the estimated prices[1] confirmed that mean price estimate correlated negatively with product familiarity (Spearman's $\rho = -0.314$, $p = .011$), product imageability ($\rho = -0.351$, $p = .004$) and mean buying frequency ($\rho = -0.470$, $p < .001$), while showing a positive correlation with market price variability ($\rho = 0.687$, $p < .001$) and no significant relation with the subjective liking of the goods ($\rho = -0.012$, $p = .924$). This indicates that products estimated as having higher prices were less familiar, had lower imageability, lower buying frequency and greater market price variation. A regression analysis between the log mean and the log standard deviation of the price estimates across participants showed strict linearity, with an estimated slope coefficient close to 1 ($b = 0.993$, $t(62) = 31.68$, $p < .001$). The Weber fraction (calculated across participants as the ratio of the standard deviation of price estimates by the mean of price estimates for each item) did not show a systematic relation with price magnitude ($r = -0.029$, $p = .821$), suggesting that the Weber fraction is independent of price magnitude and provides a good index of an item's price estimation accuracy. Weber fraction only showed a modest but significant correlation with mean buying frequency rating (Spearman's $\rho = -0.277$, $p = .027$). Hence, in our data set, as in previous studies (Dehaene & Marques, 2002), items that were bought more frequently had a smaller Weber fraction, i.e., a greater precision in the price estimate. In spite of this correlation, buying frequency alone did not explain the linear increase of the standard deviation with the mean price. In a hierarchical regression analysis, even after controlling the effects of frequency, the standard deviation of the estimated price remained linearly correlated with the mean price ($b = 0.946$, $t(62) = 25.44$, $p < .001$). Longer RTs were associated with higher price estimates ($r = 0.324$, $p = .009$), higher market price variations (Spearman's $\rho = 0.342$, $p = .006$) and lower buying frequency (Spearman's $\rho = -0.254$, $p = .043$).

Additionally, we obtained a more objective measure of the average retail price of each product as well as of its variability, by collecting the prices of these items from online and traditional stores, with an average of twenty prices per item. This allowed us to ensure that for this set of products people's estimates of market price and judgments of market price variability were realistic reflections of the actual prices. Overall, mean price obtained from stores was 34.25€ ($SD = 109.84$€, range: 0.2–698€). Mean prices estimated by the participants in the behavioural study and the mean prices obtained from stores were well correlated ($r = 0.976$, $p < .001$). Participants' price variability ratings also correlated with the price variability determined using the log of the standard deviation of the prices collected on stores (Spearman's $\rho = 0.593$, $p < .001$), confirming that people's rating judgment was a good indicator of market price variability.

2.3. Procedure

While in the scanner, participants were asked to silently read each label and mentally estimate the market price of the products. We chose this task (rather than a more explicit task such as the one used in the behavioural study) in order to avoid movement artefacts (e.g., associated with typing the estimates or with vocal responses). Each trial began with the presentation of a fixation-cross (500 ms), followed by the presentation of the item label for 4000 ms. During this time participants had to silently estimate the item's price and press a button with their left index finger when a decision had been made. They were encouraged to be as precise and quick as possible. Trials were separated by a variable inter-stimulus interval (1500, 2000, 2500 and 3000 ms) in order to optimize statistical efficiency (Dale, 1999). Presentation and timing of stimuli were controlled using EPrime software (www.psnet.com).

After the scanning session, participants were given a questionnaire in which a list of the same items was presented and they were asked to indicate the price estimate for each item. Participants also rated their own buying frequency and the retail price variability of each item, using a 7-point scale, since these dimensions significantly impacted performance (price estimates, Weber fraction and RTs) as revealed by the behavioural study.

2.4. fMRI acquisition and analysis

Scanning was conducted at Sociedade Portuguesa de Ressonância Magnética on a 3-Tesla Philips MR system (Philips Medical Systems, Best, NL) using a standard head coil. Functional data were acquired by using an echo-planar sequence (TR = 2000 ms, 34 bottom-up interleaved slices parallel to the AC-PC line, 3 mm thick, interslice gap of 0.5 mm, 2 mm × 2 mm × 3 mm in-plane resolution, FOV = 23 cm × 23 cm, matrix size = 116 × 115). Acquisition covered the entire brain. Before functional data collection, three dummy volumes were discarded to allow for T1 equilibrium. High-resolution T1-weighted anatomical images were acquired for visualization.

Preprocessing and statistical analysis of the data were performed using Statistical Parametric Mapping software (SPM8, Wellcome Institute of Cognitive Neurology, www.fil.ion.ucl.ac.uk), implemented in Matlab (Mathworks Inc., Sherborn MA, USA). Slice acquisition timing was corrected by resampling all slices in time relative to the middle slice collected, followed by rigid body motion correction. Functional data were spatially normalized to a canonical echo-planar imaging template using a 12-parameter affine and nonlinear transformation, and then spatially smoothed with an 8 mm Gaussian kernel.

We performed a correlation analysis to examine the regions that showed modulation in activity as a function of different variables of interest. The model contained four regressors: one regressor modelling the log transformed price estimate of each participant obtained in the post-scan questionnaire; one regressor for the Weber fraction, calculated across participants as the ratio of the standard deviation of price estimates by the mean of price estimates for each item (following Dehaene & Marques, 2002); and two regressors modelling the individual ratings, one for the buying frequency and the other for market price variability, both derived from the post-scan questionnaire. In this model, trials were entered as events, and price estimate, Weber fraction, buying frequency and price variability were entered as parametric modulators with linear expansion for each item. The four modulators were serially orthogonalized in order to minimize intercorrelation between measures.

Data for each participant were modelled with the general linear model using the canonical hemodynamic response function (HRF). Analysis was performed for each subject and results were combined into a group random effects analysis. Results were thresholded at $p < .001$ uncorrected at voxel level and only clusters that survived $p < .05$ FWE (family-wise error) corrected for multiple comparisons across the entire brain were considered significant. All coordinates reported are in MNI space. The MRIcron package was used for visualizing brain images (Rorden, Karnath, & Bonilha, 2007).

3. Results

3.1. Behavioural data

Fig. 1 illustrates the distribution of the estimated prices in the post-scan questionnaire. As most products were everyday items, most of the estimated prices were relatively low, i.e., less than 10€. On average, mean price estimate was 29.51€ ($SD = 101.15$€, range: 0.1–603€). These estimates were very close to those obtained in the behavioural

[1] Similarly to previous studies (e.g., Dehaene & Marques, 2002), here and in subsequent analyses we used the log transformation values because the distribution of the price estimates was positively skewed (i.e., there were more prices on the low-end side than on the high-end side), while the log data presented a distribution close to normal.

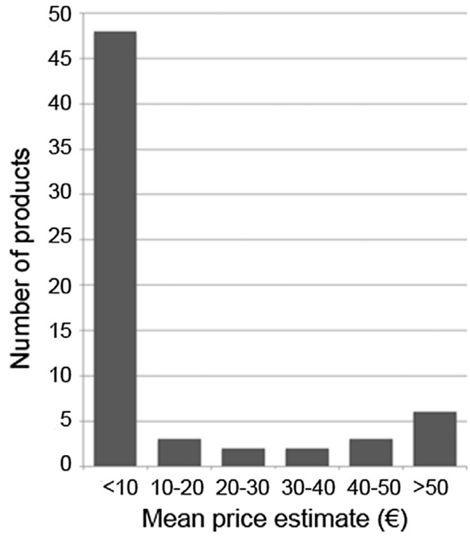

Fig. 1. Distribution of the estimated prices in the post-scan questionnaire.

study, with Pearson correlation revealing a strong and significant relation between the estimates obtained in the two studies ($r = 0.986$, $p < .001$). The estimates provided in the post-scan questionnaire were also strongly correlated with the mean prices obtained from stores ($r = 0.981$, $p < .001$), demonstrating that participants' estimates were realistic reflections of market prices.

Item-based analyses on the relationship between the log mean price estimate and the log standard deviation showed strict linearity. The log sd_i – log m_i regression was highly significant, $b = 0.995$, $t(62) = 28.07$, $p < .001$, yielding a very precise estimate of the slope, which was close to 1 (Fig. 2A). Thus, the standard deviation of the price estimates increased in direct proportion to the price being estimated, so that larger variability across participants' responses was found for increasing prices. Plotting the Weber fraction ($w_i = sd_i/m_i$) for each item against its mean price showed that although Weber fraction varied across items ($M = 0.521$, $SD = 0.289$, range: 0.12–1.58), no systematic relation with price magnitude was found ($r = -0.11$, $p = .386$). This shows that mean price and Weber fraction are independent and that the weberian relation provides a good index of an item's price estimation accuracy (Fig. 2B).

Concerning the rating judgments (in a 7 point scale) provided in the post-scan questionnaire, mean buying frequency was 2.91 ($SD = 1.02$) and mean retail price variability was 3.28 ($SD = 1.11$). In line with the behavioural study, there was a significant association between the mean price estimate and the mean buying frequency rating (Spearman's $\rho = -0.497$, $p < .001$), indicating that products estimated as having higher prices had lower buying frequency. Mean price estimate also correlated with the mean market price variability rating (Spearman's $\rho = 0.727$, $p < .001$), denoting that products with higher estimation prices had greater market price variation. When considering the Weber fraction, results showed no significant associations with mean buying frequency rating (Spearman's $\rho = -0.196$, $p = .121$) and mean market price variability (Spearman's $\rho = 0.130$, $p = .305$).

We also examined the RTs in the price estimation task carried out in the scanner. It is worth noting that in the fMRI task, RTs were a crude measure of the price estimation time, as participants had to mentally estimate the price and then press a button once a decision had been reached. Despite this limitation, on average, mean RT was 2077 ms ($SD = 605$ ms, range: 814–3775 ms). RTs showed a positive correlation with mean price estimate, with longer RTs for higher price estimates

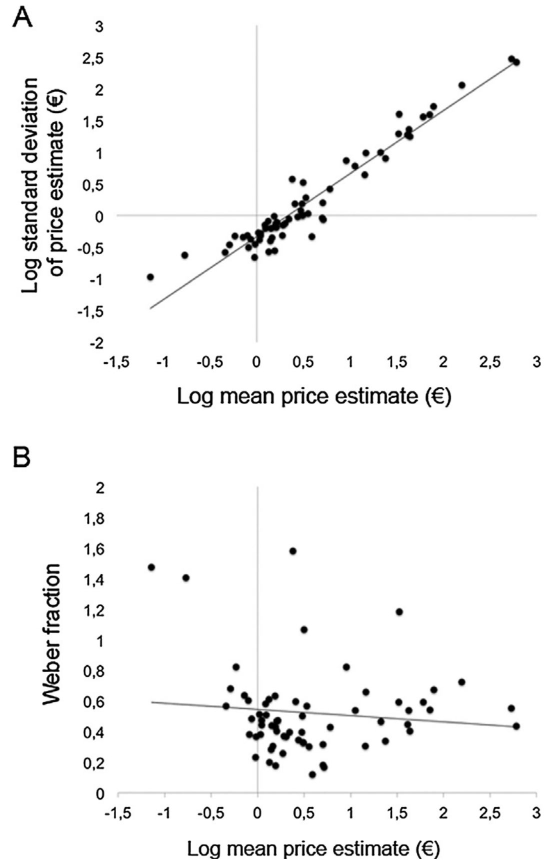

Fig. 2. Scalar variability and Weber's law in price estimation. (A) Linear regression between the mean and the standard deviation of the estimated prices across 64 different products on a logarithmic scale. (B) Approximate stability of the Weber fraction (ratio of standard deviation and mean price) across different magnitudes.

($r = 0.295$, $p = .018$), but no significant correlation with the Weber fraction ($r = -0.076$, $p = .551$). In addition, RTs correlated negatively with buying frequency ($\rho = -0.411$, $p = .001$) and had a marginal positive relation with market price variability ($\rho = 0.214$, $p = .090$). Even though RTs in the scanner were shorter than those observed in the behavioural study, presumably due to differences in the type of motor response required and to the lack of time limit to respond in the behavioural study, RTs in the two studies were correlated ($r = 0.370$, $p = .003$), suggesting that participants were responding in a similar manner. Despite not having an overt response in the scanner, altogether these results suggest that participants were performing the expected task.

3.2. fMRI data

Our main goal was to explore the neural underpinnings of market price estimation by focusing on two numerical dimensions: the size and the precision of the estimates. Increasing price estimates showed increasing activity in L medial PFC encompassing the dorsomedial and the ventromedial PFC, and the ACC. There was also increasing activity in L lateral PFC, extending to L temporal pole and a cluster in the L inferior temporal gyrus (Fig. 3A & Table 2). In contrast, decreasing price estimates exhibited increasing activation in R precuneus (Table 2).

Turning to the precision of the estimates, we found that decreasing

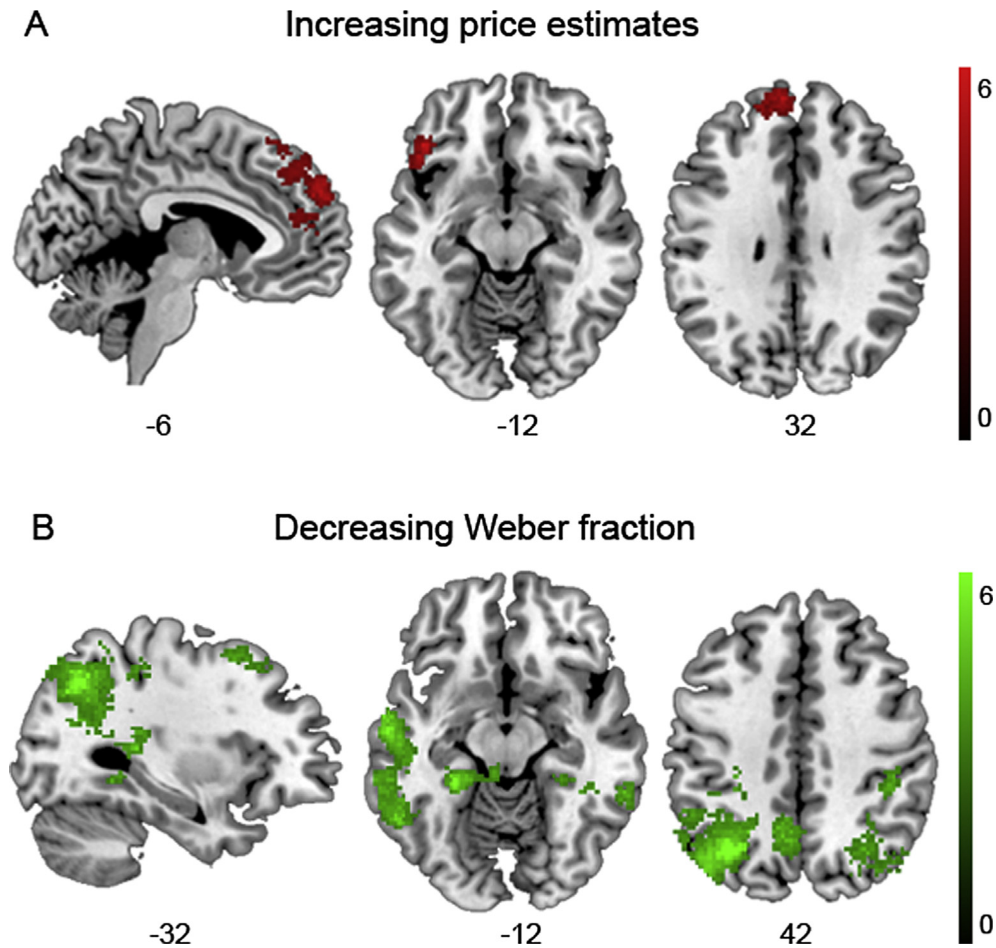

Fig. 3. Differential effects of size and precision of the price estimates in the whole brain analysis. (A) Regions demonstrating increase of response to increasing price estimates. (B) Regions exhibiting increased activation to decreasing Weber fraction. Activations are overlaid on a canonical brain and thresholded at $p < .001$ uncorrected at voxel level and $p < .05$ FWE corrected for multiple comparisons at cluster level.

Table 2
Whole brain effects of price estimation. (A) Regions demonstrating increases of response to increasing price estimates. (B) Regions demonstrating increases of response to decreasing price estimates. Results were thresholded at $p < .001$ uncorrected at voxel level and $p < .05$ FWE corrected for multiple comparisons at cluster level. The highest peak from each cluster is shown.

Region	BA	No voxels	*Z*-score	MNI coordinates		
				x	y	z
(A) Increasing price estimates						
L inferior temporal gyrus	21	120	4.77	−54	−2	−30
L lateral orbitofrontal cortex	47	474	4.70	−44	32	−12
L dorsomedial prefrontal cortex	10	823	4.43	−6	56	32
L ventromedial prefrontal cortex	10	161	3.19	−14	56	6
(B) Decreasing price estimates						
R precuneus	7	148	4.13	8	−56	52

Weber fraction yielded increased activation in a large cluster with peak in the L middle temporal gyrus, extending to the L IPS, L inferior and superior parietal lobule, angular gyrus and precuneus. There was also significant activation in the R superior parietal lobule and R angular gyrus. Additionally, there was increased activation in bilateral parahippocampal gyrus, bilateral inferior temporal gyrus including the fusiform area, and L superior frontal gyrus (Fig. 3B and Table 3). Conversely, increasing Weber fraction was accompanied by increased R inferior frontal cortex activation (Table 3). There were no regions significantly activated as a function of buying frequency and market price variability.

Table 3
Whole brain effects of Weber fraction. (A) Regions demonstrating increases of response to increasing Weber fraction. (B) Regions demonstrating increases of response to decreasing Weber fraction. Results were thresholded at $p < .001$ uncorrected at voxel level and $p < .05$ FWE corrected for multiple comparisons at cluster level. The highest peak from each cluster is shown. For the largest cluster, the highest three peaks are shown on subsequent lines.

Region	BA	No voxels	*Z*-score	MNI coordinates		
				x	y	z
(A) Increasing Weber fraction						
R inferior frontal gyrus	48	83	4.11	28	32	12
(B) Decreasing Weber fraction						
L middle temporal gyrus	21	8424	5.71	−52	−32	0
L precuneus	−23	–	5.64	−12	−58	34
L inferior parietal lobule	7	–	5.61	−32	−66	42
L medial fusiform gyrus	37	325	5.19	−26	−40	−10
R parahippocampal gyrus	36	165	5.07	26	−12	−26
R superior parietal lobule	7	305	4.71	34	−42	58
R angular gyrus	40	739	4.64	32	−52	38
Cerebellum	–	598	4.55	26	−64	−28
R inferior temporal gyrus	20	160	4.35	60	−42	−12
R inferior temporal gyrus	20	95	4.21	50	−4	−34
R superior frontal gyrus	8	181	3.98	−32	12	54

To investigate if the IPS activation overlapped with the findings of

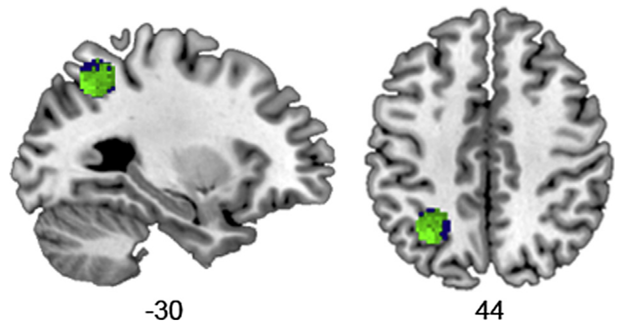

Fig. 4. Regions exhibiting increased activation to decreasing Weber fraction in L parietal cortex (in green). The mask used in the ROI analysis is represented in dark blue (10-mm sphere around the peak activation at [−28 −56 49] from Sokolowski, Fias, Mousa, et al., 2017). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Increases of response to decreasing Weber fraction in *a priori* region of interest in the L parietal cortex. Results were thresholded at $p_{\text{svc}} < .05$ (small volume correction as implemented in SPM8, i.e., FWE correction within the search volume). The highest peak within the ROI is shown.

Region	BA	No voxels	*Z*-score	MNI coordinates		
				x	y	z
L inferior parietal lobule	7	359	5.16	−32	−62	44

the numerical processing literature, we conducted an independent region of interest (ROI) analysis. To this end, we constructed a spherical 10 mm ROI located around the peak coordinate at [28 −56 49][2] reported in a recent meta-analysis of number processing in humans (Sokolowski, Fias, Mousa, et al., 2017). The ROI covered the IPS and portions of the inferior and superior parietal lobule. In this ROI analysis, activations are considered significant for $p_{\text{svc}} < .05$ (small volume correction as implemented in SPM8, i.e., FWE correction within the search volume). Results revealed a significant increase of activation in the ROI for decreasing Weber fraction (Fig. 4 and Table 4). There were no significant activations for increasing Weber fraction and no effects of price estimates in this ROI.

4. Discussion

This study investigated how numerical processing modulates the neural bases of the estimation of the market price of goods. We built on previous research on numerical cognition that has demonstrated that the processing of magnitudes is approximate and follows Weber's law.

Increasing price estimates were associated with longer RTs, greater variability across participants' responses, and increased activation in L medial and lateral PFC. This size of the estimates effect suggests that, as the estimated price increases, the cognitive and neural demands involved also increase. Medial PFC, including the dorsomedial PFC and dorsal ACC, has been implicated in various functions, including cognitive control (Shenhav, Botvinick, & Cohen, 2013; Venkatraman, Rosati, Taren, & Huettel, 2009), conflict monitoring (Botvinick, Braver, Barch, Carter, & Cohen, 2001; Brown & Braver, 2005; Kerns et al., 2004), error detection (van Veen, Holroyd, Cohen, Stenger, & Carter, 2004), and attention (for a review see Euston, Gruber, & McNaughton, 2012). Our data suggest that these general functions may be increasingly recruited as price estimates get higher. As proposed at the outset, both the nature of the numerical representations and purchasing factors may give rise to these effects. Studies on numerical cognition have firmly established that numerical representations become less discriminable as the absolute magnitude increases, due to increasingly overlapping (i.e., "noisier") representations (Cantlon, 2012; Dehaene, Molko, Cohen, & Wilson, 2004; Piazza et al., 2004). The higher the price the more taxing it would be to estimate a specific price as higher values are represented more closely than lower ones. In addition, products judged as having higher prices had lower buying frequency and larger market price variability, similarly to prior studies (Dehaene & Marques, 2002; Giuliani et al., 2017). These purchasing variables associated with higher prices may hence require the engagement of these cognitive functions, as participants must indicate a specific price among of set of alternatives without clear evidence of which one was the most adequate.

Medial PFC has also been implicated in other cognitive functions, as highlighted by the review of Euston et al. (2012). Of relevance for the current work is the proposal that this region is tied to the computation of the subjective value of the goods, i.e., the value that an individual places on an item based on his or her own preferences and goals (Clithero & Rangel, 2014; Hare, Camerer, & Rangel, 2009; Karmarkar, Shiv, & Knutson, 2015; Knutson, Rick, Wimmer, Prelec, & Loewenstein, 2007; Smith et al., 2010). In the current study, it remains undetermined whether the subjective value attributed to the items have influenced the retail price estimations. If this is the case, then the medial PFC activity observed for higher market price estimations, albeit more superior than the regions reported in subjective valuation studies, could reflect, at least in part, higher subjective valuation of the items. Alternatively, it has been proposed that medial PFC is modulated by the stimulus' saliency (Litt, Plassmann, Shiv, & Rangel, 2011). Items that are seen as more important or more arousing allocate more attentional and motivational processes, which in turn recruit the medial PFC (see also Kouneither, Charron, & Koechlin, 2009 for another perspective on the role of this region in monitoring motivationally salient events). Products that are judged as being more expensive may also attract more attention and lead to higher levels of arousal. The observed activation in medial PFC may therefore relate to saliency signals. A limitation of the current study is that it did not include the necessary controls to test these and other hypotheses directly, and so the specific nature of the PFC activity in estimating higher prices remains uncertain. Nevertheless, the finding of activation outside the IPS in a task that requires the estimation of numerical quantities points to the role of other regions, notably the PFC, in the processing of magnitudes (Ansari et al., 2006; Emerson & Cantlon, 2014; Rivera et al., 2005), at least in the case of prices.

Turning to the Weber fraction effects, our behavioural results showed that price estimation followed Weber's law: the standard deviation of price estimates was directly proportional to the mean price. This is in line with extensive research on numerical processing (2007; Ansari, 2008; Cantlon et al., 2009; Dehaene et al., 2003; Piazza et al., 2004), and replicates previous work on price estimation, confirming that price processing presents the signature property of the internal representation of numbers (Dehaene & Marques, 2002; Marques & Dehaene, 2004; Whalen et al., 1999). Additionally, we found that the neural regions that supported price estimation overlapped with those that mediate numerical processing. The bilateral IPS and adjacent parietal regions were increasingly engaged as the accuracy in price estimation increased (i.e., as the Weber fraction decreased). The ROI analysis carried out on the L parietal cortex, defined independently on the basis of a recent meta-analysis of number processing in humans (Sokolowski, Fias, Mousa, et al., 2017), confirmed the extensive overlap between the activation found in our task and that observed in numerical processing tasks. This suggests that the neural signature of the Weber fraction, previously observed for other magnitudes, such as numerosities, size, time and luminance (Clanton et al., 2009; Pinel et al.,

[2] The Talairach coordinates reported in this study were converted into MNI using the Lancaster transformation tool (icbm2tal; Lancaster et al., 2007).

2004), extends to price judgments with IPS tracking the accuracy of the numerical representation of prices.

Lastly, we did not find specific activations as a function of the buying frequency and market price variability ratings. As mentioned above, these ratings were significantly correlated with the price estimates: buying frequency showed a negative correlation while market price variability presented a positive correlation with the mean price estimates. It is thereby possible that any neural effects associated with variations in these dimensions were observed in the price estimate results.[3]

In summary, our findings provide evidence on how people estimate the market price of products. Activation in medial PFC correlated with the size of the estimates, while activity in the IPS and surrounding parietal lobules reflected the precision of those estimates. The results highlight the role of numerical dimensions in price cognition.

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[3] Note that the buying frequency and market price variability regressors were entered into the model after the price estimate and the Weber fraction parameters. In SPM a given parameter only accounts for variability that is not accounted for by the previous parameters.

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