Consistent Consumer Responses To Price Changes

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Abstract

A variety of exploratory laboratory–style tests compared brand–choices at different controlled prices. This has led to consistent findings across different brands and products (including durables and services) and other conditions.

Price elasticity, rather than being a specific characteristic of a brand, varied consistently with the competitive context, such as proximity to competitors' prices, brand share, how overt the price change was, and consumer characteristics such as being younger, or a light buyer of the brand. Measurement procedures affected the size of the effects, but the relative patterns persisted.

Such results can provide a grounded base for developing and testing pricing hypotheses.

Keywords: Pricing research, Price elasticity, Pricing experiments, Reference prices

1. Introduction

This paper reports on an extensive study designed to explore the effects of price changes on consumer choice under a wide range of experimental conditions. This is in the scientific tradition of laboratory work which would later be followed by validation and calibration studies. The aim was to investigate whether there are consistent results about pricing that can be generalised across different conditions, such as for products, brands, price levels, movements to higher and lower price and so on. For example, are price elasticities the same for changes that move above an initial base price as they are for prices that move below, or are they consistently bigger?

The background is that the pricing literature mostly reports that price elasticities vary greatly (e.g. Telser in his classic 1962 paper reported elasticities from 0 to –19). This variation has been attributed in various individual studies to many factors such as the brand, the price level, category characteristics, frequency of discounting, market share, etc. (e.g. see Danaher and Brodie, 1999). Nevertheless, few generalisable results have been claimed, and broad understanding about how pricing works has been slow to emerge from the studies conducted (e.g. see reviews by Blattberg and Neslin, 1990; Gijsbrechts, 1993; Hanssens, Parsons and Schultz; 1990; Tellis, 1988). Textbooks often imply that brands have their own idiosyncratic elasticity, and many regression models reflect this. But Gabor (1988) long ago questioned whether the concept of a brand having a single elasticity at all times is in any way useful. As an example, in our studies we measured the elasticity of Maxwell House instant coffee as varying from –1 to –4 across 10 studies. Why is that? Are there consistent factors underlying such differences?

Against this background, we are not aware of any study that looks systematically at variation in elasticities across brands and circumstances with a view to isolating conditions that may lead consistently to different levels of price response and which might eventually lead to conclusions about the hierarchy and magnitude of effects in general. In contrast, pricing experts stress that price is very sensitive to context but without systematic findings, and some say that successful prediction of pricing effects depends on recreating the particular circumstances as accurately as possible (Blamires, 1997). Our broad hypothesis here is that generalities can be found. An analogy might be with the botanist, Linnaeus (1735), famously seeking to classify flora and fauna into species.

This classification created some general knowledge about relationships within and between species, and formed a foundation for the modern scheme of taxonomy.

Extensive use of scanner panels has facilitated analysis of in-market pricing data and led to some useful findings, such as that elasticities vary greatly around an average of about –2 (Bolton, 1989; Tellis, 1988). But it has also created a large number of "unresolved issues"(Bucklin and Gupta, 1999). Their discussion of what is generally agreed amongst both academics and practitioners from scanner panel research reveals "conflicting results" and "confusion in completely separating" for example the effects of price from the accompanying "attention-getting" activities. It is difficult to classify pricing effects from real life. This is because in-market prices either don't change much, or tend to change together, and they are usually complicated by other marketing activity. Disentangling the various factors and attributing effects is complex. As Pessemier wrote in 1960 "It appears that, so long as the market is used as the source of data, there is little hope of overcoming these difficulties". We think this issue still exists, despite advances in data availability and methodology.

Hence, in the current study, we used an experimental Central Location Test methodology in order to control and vary conditions systematically. Experimental methodology is widespread in academic work, as well as in a very large amount of commercial market research (e.g. product and ad testing).

Our methodology was developed from earlier work (Ehrenberg and England, 1990), which used a Sales Wave technique where a recruited panel of households were visited at home at fortnightly intervals and offered brands for sale. Prices were varied at successive calls. This Sales Wave method was relatively realistic since it involved actual purchase and elapsed time, but proved too expensive to conduct the broad-scale work we wanted to carry out here. Our current procedure effectively collapsed the panel into one event in a Central Location, where participants were shown a sequence of scenarios of the same four brands at various controlled prices in rapid succession. We replaced purchasing with a purchase intent question (*"Which one of these would you buy, if any?"*). Our aim was not to mimic normal choice conditions, which we believe at best to be an unreliable process (Wright, Gendall and Lewis, 1999). Nor do we expect to measure real-life elasticity levels accurately from the experiments. Instead, the purpose of the work was to discover whether there are factors that produce consistent variation in price elasticities under experimental conditions – but conditions that present respondents with "an experimental environment that is not unworkably artificial" (Pessemier, 1960). A pilot study assured us that this was the case, and replicated earlier Ehrenberg and England results (Scriven, Ehrenberg and Goodhardt, 1995).

As described in detail in Section 2, a single Test (of 160 respondents) elicited choices for ten pricing scenarios featuring the same four brands, for each of four products. In all, we carried out 30 such Tests, with 4,400 respondents in the UK, USA and Germany. The Tests covered 25 products (including groceries, durables and services), 100 brands and 1,000+ price scenarios, with various major and other minor technique variations.

By conducting many tests we were able to vary factors, such as products, brands, or prices being higher than normal or lower, in a systematic way, whilst controlling others. This enabled us to establish some empirical regularities under quite a few differing conditions, both in factors we designed into the tests and in other results that emerged from the analysis, such as size of brand, and consumers' general price sensitivity.

In the design of many of our experiments, for example, we used two different methods to expose price changes. In the first (which we call Successive Scenarios, SS) respondents saw a rapid succession of price changes for different brands of the same product. In the second, changes for brands within one product were interspersed with scenarios for other products (like a mini Shopping Trip, ST), thus effectively disguising which price had changed. Successive Scenarios *consistently* produced higher elasticities than the Stopping Trip method. This has implications about the complex way that consumers use reference criteria, other than just the relative prices available, which we discuss in Section 4.

In contrast, an example emerging from the results is demonstrated in Table 1 in Section 3, that across all sorts of other conditions, both varying and fixed, a brand has about twice the elasticity when a 15% price change takes it past the price of the leading brand (in the test), than when it does not. This, and other results, lead to the major conclusion that relative order of price is more important than relative distance.

Our over-riding conclusion is that pricing responses are context-related, but not brand specific. We found five context-related factors that consistently produced bigger elasticities, for example that elasticities are bigger for smaller share brands and when passing a local reference price. We also found three consumer groupings, for example lighter buyers of the brand are more price sensitive than heavier buyers. Equally important perhaps, a further six factors examined consistently produced no effect on elasticities.

In Section 2 we describe the methodology in some depth, and in Section 3 the detailed results. We take the somewhat unusual approach of discussing the main streams of pricing research literature only in Section 4, where we can then relate our results to the existing body of knowledge. This seems to us to enhance the connections between our empirical results-based method, and existing findings (Ehrenberg 1992).

2. The Methodology

We give an overview of our method, followed by a detailed description. The aim was to expose consumers to various choice situations under a variety of controlled conditions, without attempting to mimic the shopping process. We therefore used a traditional "Hall" or "Central Location" test procedure to measure the expressed intentions of consumers to buy a brand. Qualitative evidence from respondents' and field managers' comments, and our own observation of the process suggests respondents found the task straightforward and realistic.

The core methodology and much of the detail remained the same between all the Tests, as follows. Respondents visited a series of tables ("price scenarios"), at each of which the same four brands of one product were displayed at various controlled prices (e.g. four brands of cereal). At each table respondents had simply to respond to the on-going question *"Which one of these would you buy, if any?"*. The four brands started at their normal in–market prices "N" (mostly not the same for the different brands). Prices were then varied in such a way that each brand was shown at some point at 15% above its starting ("N") price and at some point at 15% below, on tables where the other three brands were at their starting "N" price.

Brand shares for each scenario were tabulated from the choices made. Price elasticities for a brand (e.g. at +15%) were then calculated as the percent change in choice of the brand from its starting price scenario (the "All–N" scenario) and when it was at N+15%, divided by the percent change in the brand's price (i.e. 15%). The formula used, including a slight technical adjustment, is shown in Section 2.3.

The elasticities produced were summarised as averages across various combinations of (i) the product categories, (ii) the brands, (iii) the 15% higher or lower prices, and (iv) the relative price positions (e.g. passing a reference point or not). Carefully designed experimental procedures, including replication and extensive partial replications, ensured that these averages were not merely haphazard. Results were tabulated also for sub–groups of demographic, brand and product usership, and certain experimental variables. These are the results presented in this paper.

We now describe more fully the basic procedure in the UK, the so–called "Successive Scenarios", followed by variations used, for example in "Shopping Trips", display procedures and sample composition.

2.1 The Basic Procedure: Successive Price Scenarios

Data were collected from respondents in experimental "Central Location" or "Hall" Tests. A "Test" comprised a series of choices between the same four brands, in ten price scenarios, for each of four product categories in turn (hence Successive Scenarios (SS): respondents were exposed to all the price changes for one product before moving on to the price changes for another product). 160 female respondents per test were recruited using a traditional intercept technique. Respondents were screened to be buyers of at least three of the four products in the given test.

2.1.1 Differing Price Scenarios

Within a Test, prices of each brand were deliberately varied between a normal in–market price "N" for that brand, and a higher price, mostly N+15%, and also a lower price, N–15%, as shown in Figure 1. Thus, after a short briefing on the procedure, a respondent was shown four brands of one product, each at their N price (represented by the packs on a table with a price on a small card) and asked: *"Which one of these would you buy, if any?"*

Each respondent then moved to the next table where the same four brands were shown, with the price of one brand changed by +15% or –15%, and the same question was asked (implicitly, on a self-completion questionnaire). At the next table, the price of the previously altered brand was returned to N, and another brand was changed by +15% or –15%. This was repeated - there were ten such tables - with the price of one brand shown successively at + or –15% whilst all others were at N, until all brands had been shown at both + and

–15%. Finally, the original scenario with all the brands at their N prices was repeated. This amounts to the total of ten scenarios as set out in Figure 1b.

The order of the price changes was varied, as shown in Figure 1. In "Consecutive" changes, the + and –15% changes for any one brand, A say, occurred one after the other. In "Non-consecutive" changes, changes for A were separated by ±15% changes for the other three brands. This is quite a rich variation. For example, consecutive changes could lead to more focus on a brand's price, as the same brand changes price twice in succession (*three* times including returning to N), with the second change being by 30% from one scenario to the next. Half the respondents saw the scenarios in the order 1 to 10 in Figure 1 and half in the order 10 to 1.

Price changes of ±15% (i.e. only one magnitude of price change) were used in most tests to simplify the variants. In combination with the different N prices (e.g. close together or not), this still provided an indirect but controlled way of examining different *effective* changes in price relativities. 15% was chosen because it was considered big enough to produce stable measurable results, and was not a totally unrealistic level for both cuts and increases, if perhaps somewhat larger than most real-life increases. Extending the testing to different levels of price changes can now be done more easily in future work in the light of the consistent results we have found here on the importance of relative price position.

2.1.2 Products and Brands

After exposure to the ten price scenarios for one product category, respondents then moved on to ten tables with four brands in a different product category, and followed the same procedure. In all, each respondent covered four categories (e.g. Coffee, Cereals, Toothpaste, Analgesics). Products were presented in one order for half the respondents and in the reverse order for the other half.

25 product categories in groceries, durables and services were featured in 30 Tests, as listed in the Appendix. Some categories were used in many tests to help establish consistencies for parameters such as brands per se or initial price levels. Some brands were used repeatedly. Over 100 different brands were used in total in the 30 tests. Selections of medium and small share brands were used (at least in the early tests, partly to avoid dominating choice with big brands). The spread of average, high and low "N" starting prices generally reflected the prices in stores locally.

Figure 1: +15% and –15% Price Changes
(N is a suitable Normal price for each brand)

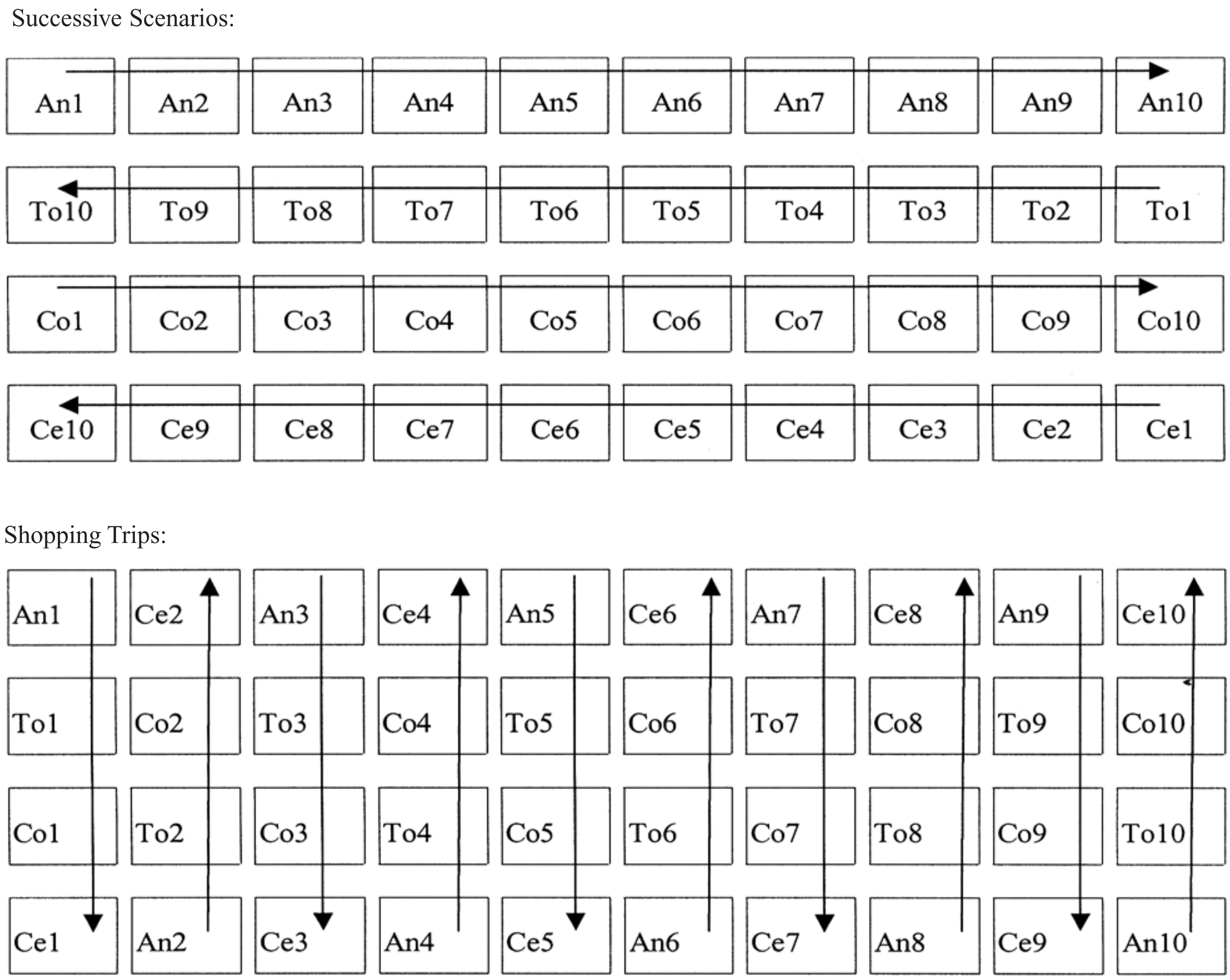
1a. "Consecutive" Changes

	"All N"				Scenarios (Tables)					"All N"
Brand	1	2	3	4	5	6	7	8	9	10
A	N_a	+15%	–15%	N_a	N_a	N_a	N_a	N_a	N_a	N_a
B	N_b	N_b	N_b	+15%	–15%	N_b	N_b	N_b	N_b	N_b
C	N_c	N_c	N_c	N_c	N_c	+15%	–15%	N_c	N_c	N_c
D	N_d	N_d	N_d	N_d	N_d	N_d	N_d	+15%	–15%	N_d

1b. "Non-consecutive" Changes

	"All N"				Scenarios (Tables)					"All N"
Brand	1	2	3	4	5	6	7	8	9	10
A	N_a	+15%	N_a	N_a	N_a	–15%	N_a	N_a	N_a	N_a
B	N_b	N_b	–15%	N_b	N_b	N_b	+15%	N_b	N_b	N_b
C	N_c	N_c	N_c	–15%	N_c	N_c	N_c	+15%	N_c	N_c
D	N_d	N_d	N_d	N_d	+15%	N_d	N_d	N_d	–15%	N_d

Figure 2: The Physical Layout of the Tests
(Arrows show direction of respondent route through the tables)



An=Analgesics, To=Toothpaste, Co=Coffee, Ce=Cereals – the same four brands of each.

1, 2, 3 etc. refer to the price scenarios as in Fig. 1

A technical question about our test design is whether the participants' claimed intention-to-buy choices would reflect real-world market shares, or be seriously biased. We found overall shares of choice at the "N" prices broadly reflected the ratio of shares of the brands concerned in the market (thanks to TNS Superpanel for market data), within the parameters of our 160 samples, and with a couple of consistent exceptions (e.g. private label) and the odd anomaly. The relevant correlations were strongly positive (.8 or .9), excluding subpatterns for private labels and special product formulations (such as Alpen, the only Muesli cereal, and Colgate Gel toothpaste, mostly the only Gel formulation in a test). Such isolated speciality brands were over-selected, we think, because alternatives offered were limited – e.g. a Tesco private label stood perhaps for any PL. More detail is available on request from the authors. All subsequent reference to brand-leaders and brand shares in this paper refers to share of choice in a specific experiment ("brand leader in the test"). In later tests, the starting "N" prices were more deliberately manipulated (e.g. to test what happened if all four brands were at the same N price).

2.2 Variations in the Basic Procedure

Major and minor differences were designed in the procedure to obtain further exploratory data, such as to test the effect of reducing the "immediate" succession of price changes for a product by introducing scenarios for other products in between (the mini Shopping Trip already mentioned). Other variations involved different display procedures in the USA and Germany; using durables and services as well as grocery products; and offering the equivalent of price cuts by extra volume free.

2.2.1 "Shopping Trips: ST"

In this method, respondents saw one table of four brands for cereals, say, then a table with four brands of instant coffee, and then four brands in each of the two other product categories (e.g. toothpaste and analgesics). They could choose a brand from each of four products in turn, as on a normal but mini "shopping trip".

They then moved on to another set of four four-brand scenarios, one scenario in each product category (in the same order as before), with one of the brands in each category having its price changed by + or -15%, as usual. And so on for another four, like a succession of "Shopping Trips", though in quick succession.

Figure 2 shows how this was achieved in practice. In SS, respondents move along the long rows, whereas in ST they move across the short rows (front to back, or vice versa). The ST method does not fully mimic real shopping procedures, but it does reduce participants' ability either to remember or to compare the price changes for any product from one scenario to another. The analysis reveals the importance of this.

2.2.2 Durables and Services

Durables and services were included in six of the tests. The sample then included men as well as women. Illustrative boards including a logo were used to represent the products, rather than product packs.

2.2.3 Additional Pricing Scenarios

In some later Tests in the UK we introduced other forms of price-cutting, such as "extra product free", usually of the order of 33% or 50% extra. These tests were replicated with the equivalent cut given in cash, and did not have a price increase scenario (i.e. no +33%).

In other later Tests, we altered some initial "N" prices, for example so that all four brands had the same N price. We also used much smaller price changes (mostly of ±2%), to test specific hypotheses about passing reference prices, as described in Section 3.2.1 below.

2.2.4 Germany and USA

Tests were conducted in Germany and the USA as additional factors in establishing whether the results generalise. In both countries we capitalised on local experience or conditions and changed both the precise test procedure and the country. The plan was to follow–up with varying one such factor at a time in subsequent work, if called for by any differences in the results, either using the original test procedure in these countries or by using the US and German procedures in the UK. Most results were sufficiently consistent across countries for additional work to be unnecessary, but we undertook some additional tests in the UK using the US method, to check an unusual result found in the US, that "SS" and "ST" methods did not produce consistently different elasticities. The US result was partially replicated in this further work, leading to the conclusion that the way we implemented SS and ST in the USA (see next paragraph), did not wholly reflect the differences in the procedure as implemented in the UK.

In the USA, because of the lack of space in modern shopping malls large enough for the 40 table displays, we used only four tables (one for each product). The price-display-cards were then changed for each scenario at the table. 400 respondents followed a split SS/ST procedure. In Germany, the price scenarios were presented to respondents via a computer display of the four packs (from a scanned photo) each with a price. 150 respondents evaluated six products using only the successive scenarios method.

2.3 The Analysis Procedure

For each price scenario (i.e. four brands at certain prices as shown in each column in Figure 1), brand shares of the claimed purchases (i.e. *"Which one of these would you buy, if any?"*) were tabulated for the four brands shown. From these shares, elasticities E_{+15} were calculated for each brand when shown at N+15% ("Higher") versus the average of the two "all N" price scenarios (i.e. as for scenarios 1 and 10 in Figure 1). Similarly elasticities E_{-15} were calculated for N–15% ("Lower").

Elasticity is here defined as the proportional change in sales divided by the proportional change in price, for a given price change for a brand. For E_{+15}, elasticity was calculated using the "mid–point" or arc formula (Buchholz, 1996)

$$\frac{S_{+15} - S_N}{(S_{+15} + S_N)/2} = E_{+15} \frac{P_{+15} - P_N}{(P_{+15} + P_N)/2}$$

where S_N = share of purchases for brand A at "Normal" price P_N. Scriven and Goodhardt (1997) discuss the issues involved in using alternative formulae.

The main elasticities thus produced are summarised and presented in Section 3 as averages across the various combinations of products, brands, 15% higher or lower test prices, experimental variations (e.g. SS and ST) and so on. This is equivalent to first establishing the "Main Effects" of the experimental design (as in an "Analysis of Variance"). We then checked that the main effects occur consistently in sub–groupings of tests, and sought to identify any interaction effects (e.g. between higher price and brand size).

Several thousand additional elasticities have also been estimated and analysed to produce the results reported here for sub–groups of demographics, usership, and experimental variables (e.g. age, brand buyers, order of price changes seen).

3. The Findings

The main outcomes of the exploratory tests are twofold:

1. To show that price elasticity is not a fixed idiosyncratic characteristic of a brand.
2. To show and to an extent quantify how the elasticities relate consistently to brands' competitive pricing context.

Five contextual factors consistently led to bigger price elasticities throughout the tests, namely when:

(i) The brand's price moved past a local "Reference Price".

(ii) The price change was easy to perceive (e.g. as in the SS method), or was explicitly signalled.

(iii) The brand's share was low.

(iv) The changed price was higher (i.e. to N+15%).

(v) The brand's normal price N was close to the average of all the brands.

Elasticities were also consistently bigger for those *consumers* who were:

(vi) Lighter buyers of the brand.

(vii) Self-classified as price conscious.

(viii) Younger.

In addition, the experiments also identified several conditions that consistently *did not* affect elasticities:

(a) All the demographic and usage variables we checked (other than vi to viii above), such as social class/income or product-category buying levels.

(b) Prior knowledge of brands' prices.

(c) TV advertising.

(d) Whether brands were close substitutes or more differentiated.

(e) Whether price reductions were in cash or kind.

(f) Most of our experimental design variables, such as order of products and brands.

Factors sometimes combined in more complex hierarchical interactions, such as that big–share brands have very small elasticities when price is cut below Normal, but only slightly smaller elasticities (compared to other brands) when prices rise above N. However, we do not yet have enough cases to analyse and understand all such interactions and hierarchies.

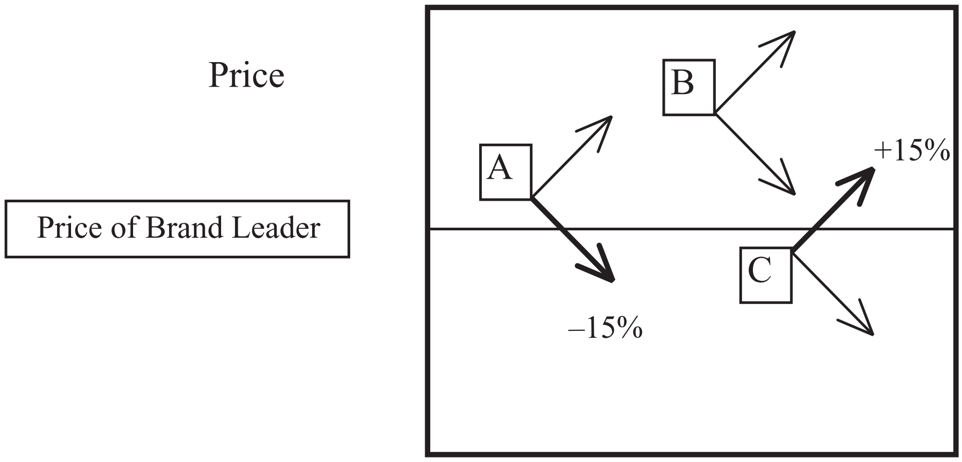
3.1 The Overall Level of Elasticities

Elasticities were almost all negative, i.e. an increase in price was associated with a decrease in sales and vice versa. The level of elasticities across all the tests averaged –3.2, with over half the magnitudes less than 2.5, and 75% less than 4. This was bigger, but mostly not dramatically bigger than the average –2 or so at times reported in real-life studies (Bolton, 1989; Tellis, 1988). The bigger values can mainly be accounted for by the pricing context we had created (e.g. when all the base N prices were the same). Extreme values were largely due to sampling and response errors. We did not expect our experimental technique to measure in–market elasticity levels accurately; nevertheless it gives a degree of external validity to know that our technique does not produce wildly different levels from real life.

3.2 Factors Leading To Bigger Elasticities

We now describe the conditions that led consistently to bigger elasticities, e.g. for passing reference prices or for small brands. Tables 1 to 10 summarise the average elasticities for all the relevant brands and tests. Some also illustrate the consistency of the results across countries, products, etc. As an example, several of the tables split the results by USA/Germany and UK "Early" (Tests 1–15) and "Later" (Tests 16–24). This embraces

Figure 3: Moving Past the Price of the Brand Leader



different countries, experimental methods, brands, prices, etc. For the UK the main difference between early and later tests was that in the early tests we set the N prices at in–market levels and used 15% as the level of price change, whereas in the later tests some N prices were manipulated for exploratory reasons, and some other levels of price change were used. The point is that the patterns in the results are the same, and this consistency mostly occurred on a test by test basis.

3.2.1 Passing Local Reference Prices

The biggest effect we found was when passing a locally defined reference price. Passing is illustrated in Figure 3 using the brand leader in the test's price as the reference. Here Brand A moves past the brand leader when its price is changed to N-15%, and Brand C moves past the leader when at N+15%. The other four moves shown do not take brands A, B, and C past the leader. Thus every price change in the test can be classified as passing or not passing.

This is a more operational use of the term than reference price in the literature, where it is used in several ways (Lowengardt, 2002), but mainly as what a consumer believes an item costs or should cost (e.g. Krishnamurthi, Mazumdar and Raj, 1992). The relationship between our definition and the more general reference price concepts is discussed in Section 4, and warrants much more future study.

We used three definitions of a local reference price:

a. The price of the brand-leader in the specific test.

b. The average of the four N prices in the test.

c. Any other price in the test (we analysed by the number of prices of other brands passed by the changing price).

These prices were not identified explicitly for participants as references. Whichever measure we used in the analyses, the notion comes through strongly of the importance of passing a perceptible reference price.

Thus elasticities were high (averaging –5.6 across all tests) when a brand's price changed from below to above the price of the brand leader, or vice versa. Elasticities were lower, averaging –2.8 (for the same average price change) when the change left the price still below or still above that of the local brand leader.

Similarly, as a second measure of local reference price, elasticities averaged –4.8 when passing the average N price of the four brands in a Test, compared with –2.5 when the price change did not pass that average.

The third use of a local reference point was to analyse elasticities by the *number* of other brand–prices passed when a price changed. Table 2 shows that elasticities were also markedly bigger the more other brand–prices were passed. Elasticities were nearly three times as big when all three other brand–prices in the test were passed, compared with none being passed.

A particularly striking case of the effect of passing a reference point came from tests where we set all four brands at the same starting price N. It was then quite apparent to our participants when a price had changed and was "out–of–line", even with a very small price

Table 1: Passing the Price of Local Brand Leader: Bigger Elasticity

Price Change Involves:	**Average Elasticity**	UK Tests Early	UK Tests Later	Germany & USA
Passing leader	**–5.6**	–4.7	–4.7	–6.5
NOT passing leader	**–2.8**	–2.4	–2.9	–3.0

Note: These results exclude the brand leader in each test.

Table 2: More Brand–Prices Passed: Bigger Elasticity

Brands Passed	**Average Elasticity** All tests
3	**–5.2**
2	**–4.0**
1	**–3.2**
0	**–1.8**
Average	**–3.2**

Table 3: Small Price Change Passing The Reference Price: Very Big Elasticities

Price Change Between			Passing	**Average Elasticity**	Coffee	Toothpaste	Biscuits	Cereals
N + 2%	and	N – 2%	All 3	**–11**	–22	–11	–8	–5
N+15%	and	N + 2%	None	**–2**	–2	–3	–1	–4
N – 2%	and	N–15%	None	**–1**	–2	–1	–1	–2

change. We implemented such a small change by moving the price of a brand also to N ± 2% (as well as the more usual N ± 15%). Elasticities averaged as high as –11 across brands for price changes between N+2% and N–2%, compared with about –2 for price changes between N+2% and N+15%, as in Table 3. (Danaher and Brodie (1999) note erratic and sometimes large elasticities for small price changes generally. Our controlled findings here for very small price changes are consistently large).

Future work can check brands for 2% price changes, but different starting prices, so that there is no passing of any prices.

3.2.2 Price Changes that were Clear or Signalled

In our "Successive Scenarios" (SS), respondents saw all the different pricing scenarios for the same product (e.g. coffee) in succession (see Figure 2). Respondents could for example quite easily remember previous prices (without the interruption of other scenarios), or even look back to check if they wished. This was expected to focus and sensitise respondents to the price changes being made. To lessen the impact of the price changes, we used in some other tests the alternative method "Shopping Trips"(ST). Respondents seeing one scenario for each test product (e.g. coffee, cereals, toothpaste, painkillers) like a mini-shopping trip, before starting the next scenarios for the four products would make it much more difficult for them to remember which prices had changed, or to look back to check.

Elasticities were consistently bigger, generally by about 1 unit, in all the scenarios using Successive Scenarios (SS) averaging –3.4, versus –2.4 in matched Shopping Trips (ST) scenarios.

To study further the effect of participants knowing that a price had changed, in two tests we explicitly indicated any price change by also showing the normal N price crossed out (e.g. 1.61 ~~1.40~~). This made a change obvious, whether using the SS or ST method. For Shopping Trips, elasticities were bigger with this signalling than without (–2.7 versus –1.6). But signalling had virtually no impact with Successive Scenarios (–2.9 versus –2.6 without signalling), presumably because participants could remember or see the non-signalled price change anyway.

The implication is that some consumers will respond to a price change when they are aware it is a change, but do not respond simply to the price change having happened. Some consumers however do not need such overt cues to respond to the price change. This ties in to issues of awareness and how consumers use reference points, and has potentially important consequences for the operationalisation of reference prices as we discuss further in Section 4.

3.2.3 Low–Share Brands

Elasticities were consistently bigger for smaller brands. Elasticities averaged –4.2 for brands with shares of less than 10% (in our four-brand test), more than twice the average elasticity for brands of 50%+ share (Table 5). The same pattern was repeated in almost every individual test. Only two exceptional cases were found — *small* elasticity for small brands. These two - sensitive toothpaste and Alka Seltzer when offered as an analgesic - were unusually differentiated (i.e. less substitutable) in function and price from the alternatives offered in those tests. But we did not find lower elasticities generally for differentiated brands (see section 3.3.4).

3.2.4 The Changed Price was Higher (i.e. N +15%)

Elasticities were about 1 unit bigger (–3.9 versus –2.6) when price rose from N up to N+15% rather than was cut

Table 4: Clearer Price Changes (SS v ST): Bigger Elasticities
Comparable Scenarios for each Product

UK Tests	Method	
	SS	ST
Cars	–6.1	–4.0
Spirits	–4.7	–4.3
Orange Juice	–3.9	–3.2
Coffee	–3.1	–1.9
Burgers	–2.9	–2.0
Biscuits	–2.6	–1.8
Cereals	–2.6	–1.7
Toothpaste	–2.4	–2.0
Analgesics	–2.1	–0.8
Average	**–3.4**	**–2.4**

Table 5: Lower Brand Shares: Bigger Elasticities
All Tests

Share at "All–N" prices	**Average Elasticity**	UK Tests: Early	UK Tests: Later	Germany & USA
<10%	**–4.2**	–3.2	–5.7	–4.0
10–29%	**–3.3**	–2.9	–3.2	–3.5
30–49%	**–2.8**	–2.7	–2.9	–2.7
50%+	**–1.9**	–1.7	–2.3	–1.7
Average	**–3.2**	–2.8	–3.4	–3.3

Table 6: Price Higher (Above N): Bigger Elasticities
By brand share in test

All Tests		**Average**	Price change to: Higher (N+15)	Price change to: Lower (N–15)
Shares	<10%	**–4.2**	–4.5	–4.1
	10–29%	**–3.3**	–3.9	–2.8
	30–49%	**–2.8**	–3.4	–2.0
	50% +	**–1.9**	–3.2	–0.9
	Average	**–3.2**	–3.9	–2.6

Table 6a: Promotional Rises and Cuts Above and Below N
(UK Tests 1–15 only)

Change is:	Between N and Above		Between N and Below		**Ave**
Price Rise	N → N+15%	–3.7	N–15% → N	–2.8	**–3.3**
Price Cut	N+15% → N	–3.5	N → N–15%	–2.7	**–3.1**
Average		**–3.6**		**–2.7**	**–3.2**

to N–15%. Table 6 shows that this differential was much more marked for big brands.

To an extent, the low elasticity found for big brands when changing to a lower price is an arithmetical capping effect. For example, a big brand cannot grow beyond 100% when it lowers its price, and in practice might be considered rather unlikely even to do that. However, a 5% share brand might triple its share to be 15%, giving a much bigger elasticity. The result remains that big brands are relatively much less responsive to lower prices.

A special (but widespread) case of price cuts and rises occurs in a price promotion, where price is cut for the promotional period, then typically rises back to the original level. Ehrenberg, Hammond and Goodhardt (1994) found that sales also return to original levels following a price promotion, implying elasticity is the same for rises and cuts *in this situation.* We found the same result, as shown in Table 6a.

The complication is that the rises and cuts in the promotion case are between the same two points (e.g. from N to N–15% then from N–15% to N) whereas those shown in Table 6 relate to prices moving higher or lower from the same starting point (e.g. N to N+15% versus N to N–15%). Table 6a (penultimate column) shows that the elasticities for a cut from N ➔ N–15% and for a rise from N–15% ➔ N are the same (–2.7), but smaller than the elasticities going between N and the higher N+15%. The deciding factor is the starting and finishing point, not whether the move is itself a rise or a cut.

3.2.5 Normal Price Near Average

For brands that had their initial price N close to (within 5 percent of) the average of all four N prices in that test, elasticities were markedly bigger (see Table 7). Elasticities were smaller as a brand's N price was further away from that average. Elasticities are therefore bigger when brands are in close price competition to start with. This might be expected from the findings about passing reference prices, as passing is more likely to occur when prices start close together. The finding is also consistent with the existing literature on neighbourhood pricing effects (Sethuraman, Srinivisan and Kim, 1999).

3.2.6 Light Brand-Buyers, Price-Sensitives and Younger Consumers

Elasticities were consistently bigger amongst these three groups of consumers, as shown in Table 8. Price Sensitive consumers are those who identify themselves, when asked at recruitment, as more likely generally to consider prices when shopping. We used a simple question which contrasted "mostly buying preferred brands regardless of price" (not price sensitive) with "shopping around and choosing brands I like at good prices" (price sensitive) and "buying the cheapest available". About 10% to 15% classified themselves in the latter category, which proved too small to analyse reliably, and they are omitted from the results in Table 8. The remaining respondents split roughly half and half into the first two groups, overall and in most individual tests.

3.3 Factors Which Did NOT Affect Price Elasticities

In contrast, the experiments showed that all the other demographic and usage groups we analysed (see Table 9), along with several other factors we now discuss, had hardly any effect on price elasticities, again consistently across brands, products and countries. Findings of no differences also aid our understanding of price effects. For example in our experiments, price sensitivity was *not* affected (perhaps surprisingly) by people's low income, heavy product-category buying, or accurate recall of prices.

3.3.1 Demographics and Category-Usage Groups

Elasticities hardly differed between certain demographic or category usage sub-groups, namely with/without children, region, social class (income), or heavy/light product buying (as opposed to *brand* buying in Table 8). This is summarised in Table 9. For example, in the Early Tests in the UK, the Elasticities for "With & Without Children", "North and South", etc. were always very close to the average of –2.8.

We note that the social class (income) result means that those on lower income are no more responsive to *changes* in price. But that does not necessarily mean that they do not have a greater tendency to buy less expensive brands.

3.3.2 Prior Awareness of Price

In later tests, we asked respondents before starting the test to provide the in-market price of a range of the test brands. This was a simple attempt to measure whether price sensitivity was greater among those who had a fairly accurate idea about product prices. In line with widespread findings (Estelami and Lehmann, 2001), most respondents were poor at recalling prices (only one response in 5 was correct to within 10%). In particular, those who classified themselves as price sensitive had no better prior awareness of price. This is not inconsistent, as people can respond to relative prices and price differences without accurate recall of market prices, as discussed in Vanhuele and Dreze, 2002.

Table 7: Brand's N Price is Close to Average: Bigger Elasticities

N price versus Average in test	**Average Elasticity**	UK Tests Early	UK Tests Later	Germany & USA
At Average (±5%)	**–4.6**	–4.5	–4.7	–4.2
Above Average	**–3.1**	–2.6	–3.4	–3.3
Below Average	**–2.7**	–2.4	–2.7	–2.8
Highest (>20%*)	**–2.4**	–2.0	–2.4	–2.6
Lowest (>20%)	**–1.9**	–2.6	–1.7	–1.7
Average	**–3.2**	–2.8	–3.4	–3.3

**i.e. N is at least 20% above average of all four N prices*

Table 8: Light Buyers, Price-Sensitive and Younger: Bigger Elasticities

Sub–group		**Elasticities**
Age	Under 25	**–3.9**
	Over 55	**–2.2**
Brand Buying	Heavy	**–3.8**
	Light	**–2.6**
Price Sensitive	Yes	**–3.8**
	No	**–2.3**

There was no consistent relationship between our price awareness measure and price sensitivity in the tests, although there was some evidence of slightly lower elasticities among those who do not attempt to estimate a price at all when asked (and therefore perhaps do not even think about it).

3.3.3 Advertised and Non-Advertised Brands

We were able to classify brands as advertised in the previous two years or not (they were about half and half), using market data supplied by mediaedge:cia. The elasticities were much the same for the two groups. Market share had to be taken into account, because advertised brands are often bigger, and bigger brands have smaller elasticities (Table 5).

3.3.4 Differentiated or Closely-Substitutable Brands

In earlier work which used a more "realistic" but much more expensive Sales–Wave technique (Ehrenberg, 1986), it was found that a product category such as biscuits, where all the test brands were somewhat differentiated (such as Rich Tea biscuits and Digestive biscuits), had lower elasticities than less differentiated products such as tea. This result might be expected from that part of economic theory that defines products as differentiated where they have low price elasticity.

To check the result more widely with the current methodology, we designed several tests with brands in pairs of close substitutes, e.g. Frosties and CoCo Pops; Kellogg's Bran Flakes and Tesco Bran Flakes, and other tests with four more differentiated brands, e.g. Bran Flakes, CoCo Pops, Shredded Wheat and Muesli. We used our own subjective "commonsense" definition of close substitutes and more differentiated brands.

However we did not reproduce the earlier result, and found no differences in elasticities between our differentiated and closely substitutable brands. We did find low elasticities for one or two isolated cases involving much more differentiated brands, such as toothpastes for sensitive teeth, or Alka Seltzer when offered as an analgesic. However, *cross-elasticities* were on average twice as big for the differentiated brands as for close substitutes (Watson–Gandy and Scriven, 2000). The implication is that the presence of more directly substitutable brands does not influence the size of response to a brand's own price action, but it does affect where switched purchases come from or go to.

3.3.5 Cash Discounts or Free Product

In five matched tests we offered price cuts either as extra product or as cash (e.g. 50% cash cut equals a "two for one" offer). Over all the cases, the elasticities averaged out the same, although with some inconsistent variations as shown in Table 10.

3.3.6 Pack Sizes

We started to explore pack-size effects in some tests, either one size versus another in different tests, or mixed brands and sizes in one test. No overall consistent patterns have been found in our limited experiments so far. The complicated interaction between brand and size provides an opportunity for future work.

3.3.7 Experimental Order Effects

The order of different price changes was varied in our experimental design to check on possible biases, for example through learning effects.

The order variations were:

1. Whether a + change (for example) was the first or the second change for a brand.
2. Whether + and – price changes were seen consecutively, or not (see Figures 1a and 1b).
3. The order in which the four product categories in a test was seen.
4. Whether a brand was the first, second, third or fourth in that category to have a price change.

None of the rotations of the order of seeing products or price changes produced a consistent effect on price elasticities. This has greatly simplified the analysis requirements and allowed us to combine results here to give more robust conclusions.

Table 9: Demographic and Usage Subgroups*: No Differences

Sub-groups		**Average**	UK Tests Early	UK Tests Later	Germany & USA
Children	With	**–3.4**	–2.8	–3.5	–3.7
	Without	**–3.1**	–2.9	–3.0	–3.8
Region	North	**–3.1**	–2.9	–3.1	na
	South	**–3.0**	–2.8	–3.2	na
Social Class	ABC1	**–3.4**	–2.9	–3.2	–3.6
(Income)	C2DE	**–3.2**	–2.7	–3.3	–3.5
Product	Light	**–3.2**	–2.8	–3.2	–3.4
Buying	Heavy	**–3.4**	–2.7	–3.1	–3.5
Average		–3.2	–2.8	–3.4	–3.3

** Excluding those in Table 8*

Table 10: Cash Price cuts versus Extra Product Free: No Differences

	Cash	Extra free volume
Orange Juice	–1.4	–1.3
Coffee	–2.3	–1.6
Cereal	–2.3	–2.2
Beer	–3.3	–3.0
Toothpaste	–3.8	–4.6
Average Elasticity	**–2.6**	**–2.5**

4. Discussion

Individual price elasticities for different brands under different conditions in this range of experimental tests varied considerably, mostly between about –1 and –4. But within this variability, highly consistent patterns have emerged.

Some conditions consistently enhanced the "sales effect", some depressed it and other conditions had no effect. Thus passing the price of another brand consistently raised price elasticities. Heavy product use, or whether a brand was advertised or not, was not associated with bigger or smaller elasticities. Such consistent experimental findings help our understanding of the pricing process.

The results confirm the long–standing doubt that a brand does not have an idiosyncratic elasticity of its own (Gabor, 1988), i.e. some absolute value for that brand which applies in almost any circumstance. Responses to price changes depended more on the context than on the brand as such. This also ties in to the findings of Tversky and Simonson (1993) on the context dependency of choice.

In all cases, changing a price had an effect on brand choice (almost all the elasticities we measured were negative). But most people, in our experiments and in real life, are not affected by any one price-change. The mechanism works through a few people changing their choice, while most carried on with the same choice they had indicated before. In our experiments, for any one 15% price change, in most cases less than 5% of all respondents changed their claimed behaviour. Those who did change were more likely to be already light buyers of the brand, and to be generally more sensitive to price. In real life, an even smaller proportion of the population could be affected by any price change, especially a temporary one, as many would not be purchasing the category at the time or would not see the change. But we believe the effects would be the same as in our experiments, only the absolute level might differ.

The experimental results go some way towards identifying the more important elements influencing variations in response to price changes. We review these now in the context of the literature.

(i) The brand's price moved past a local "Reference Price"

The extensive literature on reference prices hypothesises that consumers relate their response to price to some standard or reference point (e.g. Krishnamurthi, Mazumdar, and Raj, 1992; Rajendran and Tellis, 1994; Grewal, Monroe and Krishnan, 1998). The reference price is often operationalised as some weighted average of previous prices paid for the brand (memory based), or the current price of another brand (stimulus based, Briesch, Krishnamurthi, Mazumdar, 1997). Memory based reference seems to sit uneasily with extensive findings (including in our study) that consumer knowledge of actual prices is generally poor. However Vanhuele and Drèze (2002) argue that this is a consequence of the simplistic recall-based measures generally used, which do not measure accurately the way that consumers store and use reference relationships.

Our finding shows that the stimulus of other brands' displayed prices are clearly an important aspect of reference. However, response to price is more complex, as shown by our systematically different results using SS and ST methods for matching scenarios. Hence the notion of awareness that a price is "a bargain", which involves reference to previous own price and competitive prices, would seem to have some effect, as reflected in the literature on transaction effects (e.g. Grewal, Monroe and Krishnan, 1998). A further complication is the possible effect of 'odd prices', ending in 9 or 99, and special memorable price points, such as £1.00 (Gendall, Fox and Wilton, 1998). The empirical patterns confirm the complexity of the reference price notion, and can help to pin down operationalisation in practice.

(ii) The price change was easy to perceive (e.g. as in the SS method), or was explicitly signalled.

The signalling results more generally are consistent with extensive findings that price based (i.e. mostly feature) advertising leads to greater price sensitivity (Bell, Chiang and Padmanabhan, 1999; Bolton, 1989; Bemmaor and Mouchoux, 1991; Kaul and Wittink, 1995 (and references therein)).

(iii) The brand's share was low.

Danaher and Brodie (2000) find smaller elasticities for big brands to be one of three consistent factors in their multi-category study, as did Bell, Chiang and Padmanabhan (1999), Bolton (1989) and Guadagni and Little (1983) in their paper on logit modelling in marketing.

There seem to be no reports of contrary findings on brand size effect. This seems consistent with many other findings in marketing that brand size is a major factor to be considered (such as when studying loyalty; Ehrenberg, Uncles and Goodhardt, 2004).

(iv) The price changed to a higher level (i.e. to +15%).

Perhaps unsurprisingly, there is far less research or discussion on price increases than price cuts especially short-term promotions. A few studies do compare 'gain' coefficients to 'loss' coefficients (e.g. Bell and Lattin, 2000; Hardie, Johnson and Fader, 1993) but many studies assume that elasticities are the same for both, which we have shown is not the case. Studies of asymmetric price competition (e.g. Sivakumar, 1997; Sethuraman, Srinivisan and Kim, 1999) might seem to address this, but it seems to us are really about brand size and passing effects. Prospect theory (Kahneman and Tversky, 1979) advances hypotheses about risk aversion and the carriers of value that would lead to bigger elasticities for price rises, in line with our findings.

(v) The brand's normal price N was close to average.

Sethuraman, Srinivisan and Kim (1999) find neighbourhood pricing effects (bigger cross-price effects between brands that are immediately adjacent in price), which seem consistent with our finding that elasticities are bigger where brands are in close price competition to start with.

(vi) No effect for most demographic and usage variables, except light brand users, younger, and self–defined generally price conscious.

Bell, Chiang and Padmanabhan (1999) also show very little in the way of demographic effects on elasticities in their results, in line with the bulk of our findings (other than age). Hoch, Kim, Montgomery and Rossi (1995) find that low income consumers have bigger price elasticities, which seems to conflict with our finding of no difference in elasticities for income levels. Many logit based studies use latent classes of respondents who are more or less price sensitive but without defining the latent characteristics of the groupings. We have found no other studies that show that previous light buyers of the brand, and those defining themselves as price conscious are the most responsive to price changes.

(vii) No effect for brands with TV advertising

Our findings that brand advertising does not produce any effect on elasticities run contrary to the conclusions of Kaul and Wittink (1995), who cite nine studies that find advertised brands are less sensitive to price. However they also cite five studies with the opposite finding. It seems to us that most of the evidence in the literature of advertising affecting price sensitivity is equally equivocal. One question is whether studies reporting lower elasticities for advertised brands are actually capturing effects due to brand–size, given that advertised brands are often bigger.

5. Conclusion

Our experimental study has produced elasticity levels that are reasonably coherent, at about –2 to –3 on average, with those produced from in–market studies. The patterns of variation show conditions that lead to greater or lesser response to price, within the range of the experiment, and give an indication of by how much. The consistency of the results across all the tests, and the existence of similar findings across a broad range of other studies, shows that we have been measuring genuine factors that affect consumers' response to price changes. The conclusions can be validated further through other isolated consistent results including in real life, or in specific experimental designs, preferably of a different type. Nonetheless, the simple test procedure worked well, and the consistency of the findings so far

Appendix: Products Covered in Tests

Analgesics	Chocolate	Newspapers
Beer	City Breaks	Orange Juice
Biscuits	Coffee	Petrol
Body Lotion	Credit Cards	Satellite TV
Burgers	Detergent	Shampoo
Cameras	Eggs	Soup
Cars	Face Cream	Spirits
Cereal	Flights	Toothpaste
	Mobile Phones	

can give direction and provide benchmarks to evaluate pricing factors more widely.

An example of the benefits of having prior expectations based on empirical generalisations was that initially our US results were quite different from those we had already seen elsewhere in the study. As firm believers in Twyman's Law ("Any figure which is different or interesting is usually wrong"), we checked and rechecked and eventually revealed a pervasive coding error.

Some of the practical implications for managing prices, consequent on the results of our study are:

1. The biggest sales changes come from passing a major competitor (e.g. a closely–priced brand, or a big brand).
2. Big brands, expensive brands and private label brands are particularly unresponsive to having their prices lowered.
3. In contrast, small brands respond most to price changes, up or down.
4. More *light* brand buyers react to a price change. This links with the previous point, as small brands have more light buyers.
5. Pricing effects are enhanced if consumers are aware that a change has taken place.

Finally, we emphasise that we do not expect to be able to predict price elasticity from our study or methodology, rather to understand the factors that do and do not affect elasticity, and from that to gain insight into how pricing works.

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Acknowledgements

Thanks to Steve Long, Wendy Schlaeppi, Carl Watson-Gandy and Tom Macnamara for assistance with data analysis. Also to Heinz, Kelloggs, Laser, Safeway, Frische Vlag and IDV in Europe, and to Colgate, Kraft, Market Facts, Pfizer, P&G and Tropicana in the USA for financial support for the original project, and to 90 other companies who supported follow–up work as part of the Research and Development Initiative (R&DI) at London South Bank University. Also, thanks to two anonymous referees for their helpful and supportive suggestions.

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