With hindsight, I was probably always aiming at findings that in themselves were both simple and generalizable. Simple, so that I and others could see the patterns in the initially often complex-looking data. Generalizable (within stateable limits), to provide validated benchmarks, possibly lawlike in due course.

But this neat aim became only slowly explicit. At first I just unthinkingly did what I did. It seemed natural—like the bits of science I had picked up at school. I didn’t set out to be different.

I read mathematics at University of Newcastle and then mathematical statistics at Cambridge University, followed by three years statistical lecturing and consulting at the Institute of Psychiatry (the Maudsley) in London.

An interest in social-science applications had begun to emerge in Cambridge. But also two aversions: to statisticians imposing complex analysis techniques on simple data and to their unnecessarily parading their second-hand mathematics.

A Brand’s Heavy Buyers

My first finding in marketing arose in the late 1950s from a practical problem with the Attwood Consumer Panel, a precursor of TNS (Taylor Nelson Sofres plc) in the United Kingdom and my first marketing employer.

The panel was reporting too many purchases of Cadbury’s Drinking Chocolate (CDC), compared with factory shipments. My boss—the first and last I ever had who knew what I was supposed to be doing—wondered whether the excess was due to the panel having too many heavy buyers of the brand (they normally are critical for sales success). Could I fit a theoretical distribution to the numbers of people who had bought it 0, 1, 2, 3, or more times, to let us excise any excess heavies?

Most people buy a brand like CDC only occasionally. I therefore tried the traditional statistical way of modelling rare events, the so-called Poisson. But that did not work too well.

So I tried a certain mixture of various Poissons (called a negative binomial distribution or NBD), which crucially allowed consumers to differ from each other (as they do), and which I had come across in Cambridge in social and biological contexts (e.g., the occurrence of accidents).

This gave a pretty good fit as seen in Exhibit 1. But the fit included all the brand’s heavier buyers—they were okay and needed no excising! So the analysis was no help with management’s biased-reporting problem, which we then dealt with in other ways.

My big research issue, however, suddenly was: Was this serendipitous fit of the NBD model just a once-only fluke?

But it did fit again much more widely though slowly (it took much work and time) for big, medium, and small brands of varied grocery-type products from soap to soup and mascara—with correlations still of .9 or so, and one persistent discrepancy that was fully explained in work by Chris Chatfield, my first doctoral student.

And also (slowly) for different countries, years, analysts, shorter and longer analysis-periods, older and younger people, etc.

Such a quantified regularity was unprecedented in marketing. So it was (and is) exciting. We had stumbled on an empirically well-grounded theory to benchmark how many people should buy any brand how often. (Was it the end of marketing’s pipe dream of just recruiting heavy buyers?)

Other regularities. The model’s underlying assumptions also led to other theoretical predictions about consumers’ buying behavior (e.g., for the period-to-period flow of “new,” “lapsed,” and “repeat” buyers of any brand and the associated buying rates). The predictions again held for very varied data, and showed what to expect from a healthy brand. The model

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avoided the in practice mostly unnecessary but widely presumed “purchase feedback” and erosion of loyalty over time.

The model’s close fit in turn supported the theory’s few underlying presuppositions. (Twenty years later Gerald Goodhardt theoretically proved its main “Gamma” assumption in Nature, one of our five contributions to that renowned science journal).

For some years we examined consumers’ buying of individual brands. (I was fairly soon joined by Goodhardt and then Martin Collins in a very productive commercial team, Aske Research Ltd., where we paid our way. All three, before very long, also served as chairmen of the U.K. Market Research Society and later became business school professors.)

**Polygamous Brand Buying**

Suddenly a U.S. company researcher, Gary Grahn, noticed that the different brands in his product category were all—big or small, etc.—bought at much the same average rates.

This simple finding was a revelation, at least once we established that it generalized to other product categories. (We still know of no exceptions.)

We had average buying rates for many brands available from our past tabulations (done for years by hand and then with Hollerith/IBM punched-card counter sorters; see Exhibit 2). But like everybody else, we had never bothered to compare them to see how they differed, because we expected no single or simple outcome. (Philip Kotler’s uniquely successful marketing text had said that marketing was complex and downright difficult.)

The result passed through three stages, over some years. First, we thought and often said that the average purchase rates of competitive brands, big or small, were approximately equal. Or “constant” plus a bit of error—about 3 or 4 annually in that product category, about 6 or 7 in another. (The approximately equal sign is to me the defining symbol of applied mathematics.)

Later we noticed that the small “errors” were rather consistent over time and hence mattered. (Calculations were done on electro-mechanical desk calculators or on handheld mechanical Curtas if at home or travelling. Slide rules were not useful. See Exhibit 3 on page 38.)

Later still, we noted a common trend in these buying rates: They decreased slightly with the brands’ market shares.

Abe Shuchman at Columbia University then identified this slight trend with William McPhee’s “double jeopardy” (DJ) phenomenon in quantitative sociology: A smaller brand has,
of course, fewer buyers than a bigger brand, but the brand is also bought somewhat less often by them, because it has more exposure to competition!

**Brand switching.** Other empirical regularities in people’s buying of competing brands also slowly emerged (partly while visiting at the University of Warwick, and at Columbia during the 1968 student riots). This led to a picture of consumers of branded grocery-type products as polygamous, with several steady partners (i.e., brands), some consumed more often than others. Two examples:

- In a year, very few buyers of a brand are 100% loyal to it. Nor do they buy it often. They therefore have few opportunities for being disloyal! Marketing’s common target of “more loyal buyers” was seen to be deeply unreachable.

- How many customers of brand A also buy brands B or C in the analysis period varies directly with how many buy B at all, or C at all. This was sanctified as the “duplication of purchase law,” with a simple adjustment later for any partitioned market. (The then-intricate data tabulations were done by Goodhardt scrounging time on an Atlas at the U.K. Atomic Energy Laboratory—one of the world’s three largest computers.)


In 1970, I was recruited by London Business School (LBS) to be professor of marketing and communication, never having read anything on either subject. I stayed 23 years and learned, followed by 10 or more at London South Bank University.

**Family Background**

I had had no great urge to be a professor. My extended family had “been there done that”—a dozen or more professors (including the Regius chairs of history at both Cambridge and Oxford and a Nobel physicist); and lifelong friends like the influential Heidelberg psychiatrist Viktor von Weizäcker (uncle of the late German President) and his wife Olympia; cousins such as Franz Rosenzweig (the leading early-20th-century philosopher of Judaism) and Ashley Raeburn (former treasurer of Shell and vice-chair of Rolls Royce for 15 years); Martin Luther longer ago; and also some more public performers like Olivia Newton-John and the great U.K. comedian and author Ben Elton.

In 1939 my close family and I, age 13, sought U.K. asylum from Germany. My mother (who was what I had learned to call Aryan) had married a dishy Heidelberg professor of philosophy just before World War I. He had already become a Christian, and after the army trained for the ministry, selecting one of the bleakest of the black parishes in the Ruhr, Germany’s coal-mining region. (My mother became good at telling Jewish jokes.)

By the early ‘30s, my father had become a prime non-pin-up for the democratically elected government party (a strongly opposing Lutheran and ecumenical clergyman, an intellectual, an academic, a scribbler, und der Jude (Jew) Ehrenberg). In April 1939, he was unexpectedly released from his concentration camp (Berlin-Sachsenhausen), through bribery by the then-eminent Bishop of Chichester George Bell (as I only recently learned from my father’s two-volume biographer, Professor Günter Brackelmann).

In England now, my father was interned by the Brits for some months as an enemy alien. After that he toured the United Kingdom preaching with a strong German accent. As always he wrote a lot, typing fast with two fingers: 300 articles and many books from earlier on are on Google, and there are more. But he was also a people person.

After the war, my parents returned to Germany, where my father felt he still had tasks to tackle. (A high school was founded in his name by the former U-boat captain and headmaster Karl-Heinz Potthast.) My late sister, having gone to India as a missionary hospital matron, married an Indian theology professor, Elavinakuzhy John, and one of their daughters and her husband are now professors in New Delhi.

In Newcastle much earlier, I had met Clemency (the daughter of one of my math teachers, I discovered). We happily married, and after three years in Cambridge have lived in Dulwich, London and had three children, Stephen, Carey, and Deborah, and six grandchildren!

As a young boy, my mother had told me various funny— all very brief but quite deep, as I recognized much later. (She had always just let me think about them). One introduced me to the typical cause-and-effect argument in popular medicine: She said she had had two great uncles. One smoked two cigars every day and died at age 83. The other never smoked in his life and died when he was 2 years old.

**Sponsors**

Over the years, our research was generally supported by industry, especially Unilever and Beecham (GlaxoSmithKline) to begin with, and Esso, Shell, J. Walter Thompson (JWT), General Foods-Kraft, Mars, Cadburys, Heinz, General Motors, CBS, and a good many others on both sides of the Atlantic.
Recently we have been running our work as the R&D Initiative at London South Bank University and the Marketing Science Centre of the University of South Australia in Adelaide, with Byron Sharp there as R&DI director now. Numerous companies can share and discuss our results early.

A Super-Theory

Back in the later '70s we now needed, if possible, one super-model to account for both our many empirical repeat- and multi-brand-buying regularities.

After some thought, Goodhardt and Chatfield realized that, in brief, our empirical generalizations could all be “predicted” by combining the earlier model for repeat buying with the so-called Dirichlet distribution to cope with brand choice (a mix of not very far-fetched beta distributions).

Unlike other theories in marketing, this Dirichlet model requires only one statistical input for each brand (its market share) but has many validated outputs (with one persistent and still unexplained but minor deviation).

Marketing mix inputs like advertising, product or service quality, and price changes were not needed in modelling the usual near-steady markets. We felt, and feel, that dynamic situations are better analyzed separately, against the model’s steady-state norms. Some longer-term erosion of loyalty was, for example, isolated later in just this way by Robert East and Kathy Hammond.

However, I also realized slowly that our kind of theorizing—which describes and explains already-known and wide-ranging empirical regularities and which thus post-dicts them—was anathema to many academic marketing colleagues in the United States. (They espoused complex-looking econometric procedures, with a recent Nobel citation rightly not referring to any generalized empirical patterns that had been predicted and established.)

Sadly, there has been little academic dialogue over the years. Was I too outspoken?

Attitudinal Beliefs

We also tackled consumers’ attitudes from the mid-1960s on, with Michael Bird for JWT in London and New York, and later with Patrick Barwise at LBS. Would attitudes—what people feel about brands—also follow simple and generalizable patterns?

Not yet knowing what specifically we were looking for, we first slowly established that consumers’ expressed intentions to buy a brand, in fact, foretold its past purchases, and hence also its future ones if they were the same. But not any future changes.

Users of a brand usually liked it (i.e., ticked evaluative questions like “tastes nice”). That shouldn’t have been news, but was. For example, the then universally measured “appreciation index” (A.I.) for U.K. TV programs was just platitudinous:

“People mostly said they quite liked what they watched. And they mostly watched what they said they quite liked.”

We also found increasingly that competing brands had much the same “image” among their users, notwithstanding David Ogilvy. Users of brand A would feel about A pretty much what users of B felt about B, at least for “evaluative” beliefs (“tastes nice,” rather than the descriptive “is blue”). This made sense (to us) since competitive brands generally copy each other’s advantages, whatever people may say about brand differentiation.

An extensive attitudinal repeat-interviewing study (with Neil Barnard and Patrick Barwise and later Francesca Dall’Olmo Riley) showed inter multa alia that:

People’s attitudinal repeat responses wobbled “stochastically” over time (as if randomly), like their buying behavior.

Interviewing respondents did not condition them subsequently (long an industry-wide nightmare).

For systematic attitude shifts, various indications were that attitudes changed after behavior.

Numeracy and Literacy

In the early 1970s, Stephen King of JWT (the progenitor of campaign planning) wrote that “Andrew Ehrenberg has green fingers for data.” This seemed at first oddly absurd. Surely the patterns and exceptions in our data were obvious—anybody like King could see them (if they looked).

But I then realized that no one (myself included) had given explicit guidelines for how and why we had to set out
our own tables of data so as to make any patterns in them self-evident. Making this tacit know-how explicit took much time and effort. (Thank you, Stephen.) It ended up as my Data Reduction book, followed by the briefer but still quietly-contrarian Primer in statistical methods, and two popular videos for hire:

For any table of data, drastic rounding and ordering its rows and/or columns by a measure of size always make the data vastly more graphic (John Tukey’s “inter-ocular”—hitting you between the eyes. Or green fingers for everyone).

Few people, if any, can divide 35.2% by 17.9% in their heads (without mental rounding). Two mathematicians in a seminar at Purdue University years ago said that they could. But they gave different answers, so at least one of them was wrong. Yet when rounded to 35 and 18, one number is obviously about twice the other. The fault—lack of numeracy—is not in ourselves, dear Brutus, but in our data.

For statistical graphs, we noted that verbalizing for example a line-graph’s wiggly messages (e.g., by saying “sales mostly went down”) worked wonders for the struggling onlooker. Verbalizations were also remembered far better than even the most explicit wordless pictures (like Exhibit 1 without the “agree” caption).

Tests of such precepts were carried out with Chuck Chakrapani, and some theoretical explanations came from the vast pre-neuroscience understanding of memory processes. The great Herbert Simon had, for example, reported that people could not remember numbers of more than two digits if they were interrupted in any way, even by merely their own thoughts! As my LBS colleague David Chambers said when showing me Simon’s monograph, that explained my enthusiasm for drastic rounding and Simon’s Nobel Prize.

For writing technical reports, where I had long learned much from Helen Bloom, we developed precepts such as, in brief:

Start at the end. (Give the main findings first.)
Revise seriously. (This pre-obituary is for example the last of some 25 revisions: ars est celare artem—the art is to conceal not just the art but also the laborem.)
Barwise’s great simplification of the “fog factor”—to keep one’s long words few (three or fewer words of three or more syllables per average sentence).

**Repeating Patterns**

Over the years, we found that the earlier theoretical Dirichlet buying patterns as for soap and soup recurred for gasoline (with John Scriven), aviation fuel contracts (with Mark Uncles), ready-mix cement (Goodhardt), store choice (Kau Ah Keng), and recently (with Jay Singh and Goodhardt) different category variants like flavors or pack sizes as in Exhibit 5 (with the O and T, based just on the variants’ market shares, typically correlated .99). And for general practitioner prescriptions (Philip Stern), computers, impulse purchases (Colin McDonald), TV viewing, and price changes. This was remarkable (i.e., worth remarking on).

And similar looking, but fundamentally different, patterns of repeat buying and brand switching occur in financial and other “subscription” markets (Byron Sharp, Malcolm Wright, and the ubiquitous Goodhardt), for the makes and types of cars which motorists will buy next, in the United States, United Kingdom, and France (with John Bound and Dag Bennett), and for TV sets in China (every fifth baby and one in four new TV sets is Chinese per Bennett).

**TV viewing.** The studies here were extensive, initially with Tony Twyman, and then very much with Goodhardt, Collins, and later Barwise, with more than 100 reports for the IBA (Independent Broadcasting Authority) in London, the Markle Foundation in New York, and then the BBC. And two books.

The TV viewing patterns we found were often already familiar to us from people’s brand choices (e.g., DJ for program choice and channel choice). Many of our patterns however went counter to common expectations. Thus people were not “all glued to the box”—week by week repeat viewing of regular programs with steady ratings was only 50% or so in the past (now down to 30%).

A prudent questionnaire survey with Pam Mills also showed television viewers’ wide yet bounded willingness to pay so as to keep their terrestrial TV channels (broadly replicated later in Canada, the United States, Japan, and by the BBC now).

Our wider-ranging TV findings countered Margaret Thatcher’s determined attempt to privatize the BBC. Some are being updated for the current polychannel situation, with the detailed findings from the ‘70s as fantastic benchmarks for how it was.

**Price.** In the ‘80s, our studies of price differences and price changes were opened up by effective though expensive in-home experimentation with Len England.

Less costly laboratory experiments, then developed with Scriven, generated consumer responses to more than 1,000 price-scenarios under controlled conditions, including for some durables and services. Price elasticities were found not to be specific to a particular brand or product (like in the classic “X has a price elasticity of −2.4”). Instead, the sales effects of price all varied with the context, differing for example for prices going up or coming down, or when passing a reference price.

Scriven also established from scanner-panel data that consumers had Dirichlet-type repertoires of acceptable price bands.
Other Practical Applications

Over the years, our findings were also applied to various other marketing issues, ranging from new brands to advertising:

- **New brands.** Having one day declined an invitation from Jim Figura at U.S. Colgate to hold an in-house seminar on new brands (since we then knew nothing special about them), the realization struck overnight that our theoretical Dirichlet norms would of course show what to expect for a new brand, once it had “settled down.” (It became our most popular seminar topic for some time, with repeat performances, for example, at Procter & Gamble’s Cincinnati headquarters and elsewhere.)

  Much later, scanner-panel analyses with Goodhardt showed that consumers’ loyalty to successful new brands unexpectedly settled down almost instantly, with no settling down or “learning” period.

  This was, in fact, not totally new. Three isolated cases of near-instant loyalty for new brands (one case ours) had previously been dismissed by us and/or others as obvious aberrations. But these earlier findings had in fact gotten it right.

- **No brand segmentation.** An emperor’s-clothes check of brand segmentation showed that there wasn’t any—competitive brands appeal to much the same kinds of consumers, according to extensive large-sample target group index (TGI) data with the TGI’s 200 potential segmentation variables across 40 industries. The paper in 2000 with Rachel Kennedy received one of our five “best paper” awards around about then.

- **Price promotions.** Scanner-panel analyses of the widely used price promotions with Kathy Hammond and Goodhardt explained why such promotions do not attract increased sales afterwards.

- **Advertising.** In brief, our views are:
  1. Few advertisements are strongly persuasive, or even try to be so. (Pam Mills checked this out empirically with professionals and consumers, for TV, print, and outdoor.)
  2. After extended discussions with Neil Barnard, Bloom, Kennedy, and others, we saw advertising as mostly “mere publicity” for the brand, to remind knowledgeable consumers (with ads resplendently saying “Coke is it” when all consumers already knew Coke). Ads might occasionally also nudge towards a purchase.
  3. A brand’s salience seemed key: Any propensity for the brand to come to mind or be noticed (developed further by Jenni Romaniuk and Byron Sharp).

No Statistical Techniques

As a quondam statistician, I have never found any use for the various widely accepted statistical analysis techniques such as least-squares regression or factor analysis.

One reason is that these techniques have not led to a single lasting scientific discovery over the last 100 years or more. (Other reasons are technical.) In contrast, we have been finding plenty of generalizable regularities without these techniques, like other normal non-statistical scientists.

My earlier technical doubts from Cambridge days were fleshed out in various papers (some unduly long), with constructive counter proposals. These were continuously applied in our own work and discussed in many seminars, at the Massachusetts Institute of Technology, the then-glamorous Bell Labs, and more (preaching what we practiced).

Over the years, we have also never sought to quickly justify our results as being “statistically significant,” as many data analysts still seek to do. Instead, each of our results had been empirically replicated by hard slog for different brands, products, countries, years, etc.

In the ’90s, these things were checked further with our Car Challenge (partly while visiting at New York University): Some 30-plus leading modellers worldwide were invited to apply their own preferred statistical analysis procedure to some simple two-purchase repeat-buying data for new cars (the new make acquired and the previous make). The data were replicated with very large samples in two countries and for each of four years.

We found, mainly with Richard Colombo, that the 20-plus participating modelling experts gave almost 20-plus individually differing answers—to justify themselves? Many tackled only one of the eight data sets: Few therefore checked whether their initial finding was reproducible, heading fast toward cold fusion.

Sum Ergo Cogito

Inverting, as a humdrum scientist, the famous philosopher’s “I think therefore I am,” I still see my emphasis to have been on results which were generalizable and simple (and hence often beautiful).

I do not see very many uncorrected mistakes in what we did (critics have perhaps been too kind). But I have become increasingly aware of gaps.

Additional Reading

Published papers are listed in a bibliography of some 300 titles prepared by colleague John Bound at www.lsbu.ac.uk/bcim/business.

For any table of data, drastic rounding and ordering of its rows and/or columns by a measure of size always make the data vastly more graphic.