**Estimating the value of passing trade from pedestrian density**

1. **Introduction**

Retailers pay great attention to footfall. Its density defines the economic viability of any trading location (Timmermans, 2004) influencing both the supply and demand side of the retail environment (Brown, 1994). On the demand side major store brands and developers can establish likely turnover from a potential development using macro-level geo-spatial interaction models which balance attractiveness, competition and the catchment boundaries of friction distance (Converse, 1949; Ghosh and Craig, 1983; Huff, 1964; Reilly, 1931). For any established retail location, central place theory and bid rent models will define zoning hierarchies (Dennis *et al.,* 2002) by estimating footfall demand effects on rental values. Further macro-models describe variation in footfall densities across a location, for example from the siting of entry and exit points and parking and transport hubs (Timmermans & Van der Waerden 1992), the layout, landscaping and siting of street furniture (Foltete and Piombini, 2007), trip-chaining effects from the geo-spatial arrangement of the retail offer (Leszczyc & Timmermans, 2002) and the behavioural dynamics of small pedestrian groups (Wang *et al.,* 2014).

On the supply side, mall managements routinely control tenant and anchor store locations to draw shoppers past as much of the offer as possible (Carter and Vandell, 2005) and in UK town centres, although the tenant mix is less controlled, local government partnerships are increasingly initiated to maintain high street vitality (Wrigley & Lambiri, 2014).

Much is therefore known about the demand contained in pedestrian flows at the macro-level, but as Wood and Brown (2007) suggest, geo-spatial models cannot estimate micro- (store) level demand for the very many smaller comparison goods retailers, those stores selling anything otherthan fast moving consumer goods, or newspapers, alcohol and tobacco. These businesses typically benefit from only a limited catchment (Wood and Tasker, 2008) and depend upon existing footfall for turnover - passing trade. Brown (1994) and later Wood & Browne (2007) both therefore emphasised the importance of footfall observations in the site selection process, while Allport, (2005) and Pasidis *et al* (2016) suggest that smaller retailers already *in situ* can maximise demand from existing traffic, and should compete, by adopting niching strategies. While acknowledging the importance of footfall, these authors do not offer a method for smaller comparison goods retailers to estimate the likely value of passing trade from pedestrian densities.

In order for a retailer to activate the latent demand in footfall, two conversions are needed. Lam *et al* (2001) suggest a framework linking footfall density (*front traffic*), to store traffic via a *store entry ratio* and then once in-store, a conversion rate of shoppers to buyers through a *closing ratio.* Matzler *et al.,* (2010) and Perdakiki *et al.,* (2011) subsequently adopted this framework but their concern was for model building rather than establishing baselines or predicting outcomes generally. We now address the issue of deriving and testing a usable benchmark or empirical generalisation that could capture the potential value of passing trade from this conversion framework.

The study makes four contributions to retail marketing knowledge. First, it identifies benchmarks with which to evaluate competitive performance on the double conversion dimensions (store entry and closing ratios). These benchmarks will diagnose specific areas for marketing intervention, predict the performance of any competing retailer in a proposed or existing location, and can establish a basis to negotiate rent and control overheads.

Second, prior research on the model has been conducted in the US. We have extended it to three further countries, recording just short of a million pedestrian observations and around twenty thousand shopper conversions to establish, we believe for the first time, that sales in a given period at any existing or proposed retail store within a category can be broadly predicted from the footfall density passing outside.

Third, footfall varies by location, context and time. The replications in this study manipulated these effects in different locations and on different days, yet the conversion benchmarks continued to capture performance without recourse to moderating variables such as labour employed, brand positioning, display or store atmospherics. The ratios proposed are therefore parsimonious and simple to use.

Fourth, we show how the benchmarks are contextualised within established theory, which explains the predictable effects of brand size on observed conversion ratios and makes them more reliable and capable of delivering quite detailed insight.

1. **Theoretical Context**

Retail marketing is competitive. Consumers choose between shopping locations, between competing store brands and types, between rival brands in those stores, and between just browsing and buying. These choices are all susceptible to marketing intervention. For example, Sorensen’s (2009) Double Conversion framework describes how, in order to achieve category sales in the grocery store, aisle visitors must first become shoppers and shoppers must then be converted to buyers. This is achieved, he argues, through effective merchandising, which has both stopping power and closing power. The same Double Conversion principle has been adopted in comparison goods retailing by Lam *et al.,* (2001), Matzler *et al.,* (2010) and Perdikaki *et al.,* (2012) where the base measure for a store entry ratio and closing ratio becomes front traffic.

Understanding and predicting the volume of front traffic, how it flows around a retail location, and how its density defines a location hierarchy have each become subjects for well-known macro-level models (e.g., Brown, 1991; Primerano *et al.,* 2008). However, smaller comparison goods retailers are unlikely to have much influence on traffic volume, and in particular may not have the resources to employ sophisticated modelling techniques. These retailers often instead attempt to exploit the available footfall by building more loyal patronage, segmenting and targeting particular buyer classes (Ruiz et al 2004). In competitive settings where the pricing and range of retail offers is hard to differentiate tangibly, a positioning might then be developed based perhaps on better communication or management of customer relationships (Mulhern, 1997; Sorescu *et al.,* 2007), store atmospherics (Baker *et al.,* 1994), or store brand image. Both Das (2014) and Zentes *et al.,* (2008) identified store loyalty effects resulting from store brand personality, and Hartmann and Spiro (2005) identified further opportunity since store equity effects also carry over between on and offline choices.

Stahlberg and Maila (2010) report that sixty-eight per cent of retail buying decisions are unplanned; store entry may at least partly also result from prompting consumer impulse. To this end, Underhill (2010) urged retailers to “liberate the design team” and create enticing window displays that will be noticed even by tight clusters of shoppers – Sorensen’s *stopping power.* Advertising and promotion are also effective: Kirkup (1999) and Denison (2005) both report raised store traffic levels, (although not calculated as a ratio of front traffic) as advertising effects that may be cued by window display, or now by micro-targeting through apps and RFID technologies (Grewal *et al.,* 2011).

Once in store, there is some evidence that category effects may define the closing ratio. Yiu and Ng (2010) found conversion rates ranging between 40% and 100% across store types. Closing rates may also depend on effective labour scheduling (Perdakiki, 2011), store atmospherics again (Eroglu, 2003), and a host of category management initiatives - pricing, ranging, display and promotion – all designed to gain higher category share than rivals through better than average conversion (Desforge & Anthony, 2013).

The literature here is well developed; it argues that the antecedents and determinants of consumer choice in retail are many and highly varied, making the idea of a simple causal relationship between footfall and sales seem unlikely, or at best rather hard to model in practice. Indeed Matzler *et al.,* (2010) argues that the double conversion framework is rather too simple to explain a complex function, going on to find eighteen deterministic barriers to in-store conversion (including out of stock, did not feel welcome *etc.*).

Given the complexity of individual consumer choice behaviour, an alternative is to apply a stochastic model to describe aggregate purchasing across a competitive set. Such models usefully predict *how* (rather than why) people buy, and their use in this context is supported by the fact that individual shopper behaviour appears surprisingly habitual or at least subject to the heuristics of a bounded rationality (Gigerenzer, 2001). Dickson and Sawyer (1990) found that just under half of all shoppers spent five seconds or less at a category fixture, 85% handling one brand only and 90% examining only one size variant. One in five could not estimate the price for an item they had just put in their basket, and further work on price knowledge (e.g. Clerides & Courty, 2017; Jensen and Grunert, 2009) continues to find levels of information processing at the point of sale that would support *as-if* random assumptions when modelling behavioural outcomes.

One such stochastic model, the NBD-Dirichlet (Goodhardt, Ehrenberg & Chatfield, 1984), is highly generalised in the retail field and has successfully described habitual split-loyal buying of consumer packaged goods (Sharp et al., 2012), patronage of grocery store types (Wrigley & Dunn, 1983), grocery store brands (Keng & Ehrenberg, 1984; Knox and Denison, 2000; Uncles and Hammond, 1995), online and off-line buying (Dawes, & Nenycz-Thiel, 2014), in China (Uncles & Kwok, 2008; 2009), in high street fashion (Brewis-Levie & Harris, 2000), and in fast food in Australia and Taiwan (Bennett & Ehrenberg, 2001).

The important point however is that the model closely describes a wide range of established empirical generalisations in shopper behaviour, resulting from the surprising but commonly supported observation that the market views competing offers as largely substitutable (Ehrenberg *et al.,* 2004; Sharp, 2010) so that choices follow fixed distributions across available options. This in turn suggests that if an empirical generalisation can be found that links foot traffic to sales then it is likely to be a competitive effect. All things being equal, since the footfall on any high street or mall in a fixed period is likely to contain some proportion of category and brand users it follows that the main predictor of sales for any retailer in any category will be the volume of front traffic available. This therefore leads to the first research question:

**RQ1: Is there is a regular relationship (an empirical generalisation) between front traffic and the attraction and closing ratios in any category, such that retail brand sales can be predicted from front traffic volume alone?**

An empirical generalisation (EG) is *"a pattern or regularity that repeats over different circumstances and that can be described simply by mathematical, graphic, or symbolic methods"* (Bass, 1995). It is the role of marketing science to develop the strength, scope and limits of known empirical generalisations through systematic replication (Anderson, 1983; Wright & Kearns, 1998) and to discover new ones.

In this type of research, results normally build over time, first in the observation of low-level regularities, then in establishing, replicating and extending them into empirical generalisations and then by linking them in explanatory theory which is strengthened as exceptions are observed in further tests (Ehrenberg, 1995; 2002). On the other hand, many reported studies now rely on single datasets, and consign replication to future research, a fact which led Uncles and Kwok (2013) to suggest that business researchers might be better to start the replication process in their initial design, preferably differentiating across conditions (for example time, culture, categories) and testing generalizability in many sets of data (MSoD). This is because un-replicated findings are not easy for managers to use. There is little way of knowing if they are typical or abnormal, or may hold in the future, or under different conditions. This therefore prompts a second research question, to establish:

**RQ2: If a relationship does exist between pedestrian density and sales will it generalise under different conditions of time, category and cultural context?**

One useful and well-known empirical generalisation in marketing is the Law of Double Jeopardy, a statistical selection effect first identified by the sociologist William McPhee (1963) with many applications in situations where consumer behaviour is categorized by split-loyal choice. In marketing, the law states that small brands are punished twice. Compared with bigger brands they have fewer buyers, and those buyers buy the brand slightly less often (Ehrenberg, Goodhardt & Barwise, 1990; Sharp, 2010). A predictable DJ relationship between market share, market penetration, and average purchase frequency has been observed in a large volume of replicated empirical research (Romaniuk & Sharp, 2016; Sharp *et al.*, 2012) implying that penetration, the number of customers a brand has, is far more important in determining brand size than how loyal those customers are (Romaniuk, Dawes & Nenycz-Thiel, 2014; Trinh & Anesbury, 2015). Even though rivals may be perceived as differentiated, the evidence repeatedly shows that the behavioural loyalty they attract, however measured, varies little, and always in line with customer numbers.

Double Jeopardy depends on two theoretical assumptions; the first is that in any observation period, brand purchase incidence is independent of brand choice (i.e. buyers of Brand A buy it as often as Brand B buyers buy B), the second is that there is no difference in how often the buyers of competing brands buy the category itself on average (i.e. that no brand corners the market in heavy buyers).

Although these assumptions seem counter-intuitive, Double Jeopardy is observed to constrain the near-habitual choice outcomes between store types, stores within a category and brands within a store, defining Dirichlet market structures. Further empirical generalisations capture the near-habitual response to the shopping activity itself (Sorensen *et al.,* 2017), patterns of shopping incidence & frequency on and off-line (Anesbury *et al.,* 2016; Dawes & Nenycz-Thiel, 2014), response to end-cap displays in store (Caruso *et al.,* 2015), and private label buying across stores (Dawes & Nenycz-Thiel, 2013). These EGs reflect the behaviour of experienced shoppers and a near-universal desire for efficiency in the task (for example the mental store mapping that allows a trip to be completed faster, but restricts store coverage and unplanned purchasing from less familiar categories).

Double Jeopardy is the theoretically based and necessary outcome where individual choice repertoires are habitual and consumers experienced. Ehrenberg & Goodhardt (2002) explained this statistical selection effect using the example of a town with just two restaurants, W, which is very widely known, and O, which is just as good, but more obscure. People who know both restaurants regard them as being equally good, but fewer ever visit O just because fewer people know about it. Attitudinally, relatively few of O’s smaller customer base will say it is their favourite, while of the very many who say W is their favourite, most will do so only because they have never heard of O; of those that do know O as well W, only half are likely to say it is their favourite because W is of equal merit, and so the “vote” will be split (with some “don’t knows). Attitude and behaviour both reflect the DJ characteristic: in comparison with W, over the course of a year, O will have fewer diners, those diners will say they prefer it to W a little less often, and they will visit it fewer times than W over the course of a year.

Within a retail category (e.g. between the rival book shops or fashion stores available), Double Jeopardy is likely to affect both attraction and closing rates at individual stores because both are measures of choice where shoppers are already experienced about the options. The ratios might be expected to vary by category (since fashion outlets attract more people more often than book stores do) but if Double Jeopardy holds across retailers of the same type it will constrain the relative sales performance of those smaller less well known stores, which are often advised to set niche marketing objectives. Such objectives predict higher levels of purchasing by a few “regular customers”; whereas Double Jeopardy defines a largely similar purchase rate at all rival brands. To identify Double Jeopardy effects it is therefore necessary to compare both the conversion ratios across a competitive set in order to ascertain if (and indeed how):

**RQ3: Conversion rates at rival retail stores reflect the Law of Double Jeopardy.**

An important feature of EG research is that it does not rely on tests of statistical significance or best fit (Ehrenberg, 1995). This prompted Barwise (1995) to suggest that a good empirical generalisation should have five attributes: scope, precision, parsimony, usefulness and linkage to theory. Scope means that empirical generalisations should be routinely predictable under a wide range of conditions. Precision relates to the best possible description of the phenomenon, while parsimony relates to the quantity of possible variables that can be excluded from that description. Precision and parsimony promote usefulness by encouraging practical application of simple models among managers. An empirical generalisation is also better if it can be explained by a theory. The theory can then account for the generalisation and for its scope. Consequently, if emerging EG’s from this study define and link competitive outcomes to Double Jeopardy theory, they should also be evaluated in the light of Barwise’s four remaining principles, so that competitive outcomes should be predictable from a simple mathematical model that captures the empirical generalisation and provides a useful diagnostic management tool.

In order to address the three research questions, the paper proceeds as follows. First the method employed in the differentiated replications is described. In subsequent sections we show the data analysis, present the derivation of the empirical generalisation and demonstrate the model, contextualising the results within known theory. Finally we discuss the findings and their managerial implications, before highlighting the limitations of the study and proposing further research.

1. **Method**

*3.1 Observational research in marketing*

The study design is a natural experiment requiring observation of public behaviour while controlling and manipulating variables of location, time and subject, in order to develop and test new EGs in retail marketing. According to Bogomolova (2017) observational research is a useful technique that overcomes many of the sources of error common in self-reporting survey methods, such as memory lapse or social desirability bias. It is especially important when investigating habitual (and hence intrinsically uninteresting) behaviours such as routine shopping, since it bridges the gap between measures of intended and actual behaviour (Rundle Thiele, 2009).

The data in the study consisted of pedestrian counts and behavioural observations. Traditionally, pedestrian counts have been taken manually, but are often now made mechanically as traffic crosses a beam at a fixed point, or through CCTV, or by collecting signals from mobile devices. Mechanically derived data collection is nevertheless still validated through concurrent manual counting over short periods (Phua, 2015), and therefore given that the research design specifies fixed hourly observations, well-trained researchers were considered capable of accurate collection. To ensure face validity, and confirm method reliability, pedestrian counts were triangulated with available published footfall data (See Appendix A).

*3.2 In-Built Replications*

The research design had in-built replications by country and category, as well as by location, day and time. Three different retail categories were considered; *masstige* body care in the UK, fashion in the United Arab Emirates and fast food in Pakistan. In each category four competing brands were selected for the research on the basis of a) similar store size, b) differentiated store image and, c) each brand trading in the same comparable retail locations (for example each with a store on a prime high street, a shopping mall and a transportation terminal). Four location types were identified in the UK, and three in Pakistan and the UAE. The resulting design therefore identified 40 locations in which to conduct hourly observations, so that any regularity or variance in shopper response could be compared within brand, across location types and categories, and most important, *between* competing brands.

*3.3 Research Context: Brands and Market Shares*

In each category the observed brands were of different size. Table 1 gives national market shares, store numbers, length of market tenure and positioning summary.

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Table 1 About Here

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Relative brand size depends on market definition. The UK body care base market data included multiple retailers as well as the specialists considered here. Brand A takes about a third of the sales made at specialist stores only, but a relatively small share (reported here) of the wider category. Fashion in the UAE, as everywhere else, is highly fragmented across many branded retailers. Brand A is again the leader in this market, but with a very close challenger in Brand B. The low relative shares reflect the sheer number of retail brands in the competitive set. In fast food, there were far fewer rival brands in the data, but once again Brand A was the leading choice.

Table 1 reveals a close relationship in each category between market share and number of stores confirming that despite very different brand identities, these retailers are close competitors (i.e. largely seen as substitutable by the market), and therefore suitable for inclusion in the study. There is a less clear relationship between share and tenure but in body care and fashion the biggest brands have more stores and have been available for longer, therefore occupying more space both on the high street and probably also in people’s minds.

*3.4 Observations: Locations and Times*

In body care, observations were conducted on Wednesday and Saturday. To control for extraneous variables (e.g. weather, industrial action or major sporting events) the times and the dates were held constant. Teams of four researchers were positioned to count the front traffic (individual pedestrians passing in both directions immediately outside each of the sixteen stores) between 14.00 and 15.00 on both days, resulting in 32 observation hours (i.e four rival store brands, each in four locations, twice). Using manual counters, paired researchers recorded pedestrian flow in ten-minute intervals, and noted the numbers entering each store between the cut-off times. Purchase data was collected by proxy, either as observations of the numbers leaving with a store-branded bag, or (in most cases) where sight lines left till points visible. Tasks were rotated to avoid fatigue and mitigate for systematic researcher error. Since not all shoppers who had purchased left the store with a visible branded bag, some error may have resulted from the observations, although the sample was large, and any bias therefore likely to be slight. In the two hours, around 57,000 footfall observations were made, and about 900 individual purchase proxies recorded.

A further 326 hours of observation were made of shopping at fashion and fast food brands in three location types in the UAE and Pakistan; a regional mall, a local mall and a CBD. In Pakistan, in the fast food category, counting followed the London experiment but the closing ratio was based not on single transactions but on the number of diners. The metric provided an opportunity for convergence analysis in the replication (Uncles & Kwok, 2013). Sixty observations were undertaken in three cities, Karachi, Lahore and Islamabad between 16.00 and 17.00, on each of five days. In the fashion category in the UAE, researchers were given access to timed store transaction data and company security staff established store entry counts. Here 266 one-hour observations were conducted on Tuesdays and Saturdays across a month. Across the three categories almost a million shoppers were counted, and over 20,000 purchases recorded.

*3.5 Measures and Data Analysis*

The measures used to develop the empirical generalisations were based on the model presented in Lam *et al.,* (2001) and the conceptualisation of double conversion in Sorensen (2009, p.101). All measures are hourly time bounded to impose consistency on the eventual generalisation.

Sales potential is contained in the first measure collected, namely *front traffic.* This was expected to vary by location, by hour and by day of the week.

Retail effectiveness is then initially defined by a store’s ability to convert front traffic to store traffic, captured in a second metric, the *store entry ratio*:

$$\frac{Σwho enter the store in the observed period}{Total front traffic in the same period}$$

The ratio is expressed as a percentage. The store entry ratio is an equivalent concept to Sorensen’s “stopping power”, and describes the ability to attract attention and convert a passer-by into a shopper.

The third measure is the *closing ratio,* the conversion rate of shoppers to buyers, measured using transaction data in the UAE, or by proxy in the other studies:

$$\frac{Σ observed buying/leaving with a store bag/ dining in the period }{Total store visitors in the same period}$$

Again expressed as a percentage, it denotes the proportion of store traffic that has been converted from shoppers to buyers in each hour. The ratio is a comparative measure of sales effectiveness.

In the subsequent analyses, the principles of data reduction (Ehrenberg, 2000) were followed to reveal the patterns and regularities of competitive structure contained in a large quantity of individual counts. Results were expressed as mean hourly measures and ratios, tabulated by brand in national market share order, to compare front traffic rates at each location type by day with the store entry and mean closing ratios.

1. **Findings**

*4.1 The main patterns*

As expected, individual hourly observations showed great variability in front traffic densities between locations in the same trading hour on a weekday and a weekend. The column averages at the base of Table 2 show that weekend trading is 50% higher than weekdays. We considered comparative brand performance, initially aggregating the results from each store brand across its different locations. Table 2 thus reveals differences between rivals instead of differences between location types. Aggregating the data in this way elucidated how well each brand was competing for higher traffic locations, how effectively each brand attracted footfall, and how efficiently it converted shoppers in a typical hour across its stores.

First, it became apparent that footfall density reflects brand rank; stronger brands were continually exposed to higher pedestrian densities at store level. In body care the four Brand A locations observed benefitted from twice the front traffic of rivals’ outlets. Occupying the best locations creates a strong barrier to entry and competitive trading advantage.

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Table 2 About Here

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*4.2 The emerging empirical generalisation*

The analysis next revealed two consistent empirical results across the three categories. Although footfall differed greatly between week and weekend, store entry and closing *ratios* remained constant. In body care, whatever the observed hourly front traffic, about four in a hundred (3.8%) were attracted into the shop. Of these visitors, four in ten (42%) were converted into buyers. The fixed ratios varied in scale but generalised across the categories suggesting an emerging empirical generalisation linking footfall to passing trade.

In fashion the conversion ratio was similar to that found in body care - just under half of all store visitors made a purchase - but the store entry ratio was systematically about 50% higher. It is not yet clear why this should be. It is possible that fashion has a higher penetration than skincare in any given period, or is inherently more “browsable”. Certainly a pedestrian activity simulation model developed by Dijkstra & Jessurun, (2016) estimated higher visit probabilities for fashion over health and beauty stores in the Eindhoven CBD, while Sen *et al.,* (2002) report that fashion window displays can communicate store image information in a way that effectively prompts store entry decision. While still a question for further research, it is important to note that the uplifted store entry ratio (and hence higher customer numbers per store) is a systematic category characteristic, rather than a source of competitive advantage between rival brands.

Food service brands also revealed consistent ratios, but while the mean store entry ratio was close to the body care measure at just under 4%, the closing ratio was far higher at four in every five visitors (and thus close to the 90% conversion reported for restaurants in Yiu and Ng, 2010). The ratio reflects total meals not transactions, but in foodservice, a commitment to purchase is likely made in advance of a visit and since up to 70% of front traffic is likely contained in a group (Cheng et al, 2014) one “refusal” may represent a substantial loss of business. The surprising number is therefore the systematic 20% who did not dine. Further research will establish how this relates to available tables, the length of queues or to other factors.

*4.3 Links to other EG’s and to theory*

The passing trade EG captures the relationship between front traffic and sales quite well within a category, but it differs between categories, an important finding when establishing managerial uses. To investigate patterns and exceptions further, the data was aggregated once more to produce a mean hourly rate on each metric for each brand, combining days of the week but retaining the category distinction. In each category, correlations between footfall and the store entry and closing ratios were then calculated (Table 3), and in addition the average proportion of hourly front traffic converted to buyers/diners was derived as a category constant from the mean of the brand ratio values (e.g. the number of diners in *a typical* fast food store per hour should be .037 x 0.81 = 2.99% of its front traffic).

Correlations between front traffic and store entry ratios were positive, and greater than *r* = 0.6, a strong relationship (Cohen, 1988) that described a systematic effect - that lower front traffic was reflected in a slightly lower than average store entry ratio.

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Table 3 About Here

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Table 3, (in national market share order), showed that the biggest brands had a location-based footfall premium of about 50% over the smallest, ***and*** an additional (small) uplift against average store entry ratio of about 10% (for example KFC attracted 4.1% of its footfall against a category mean of 3.7%). By contrast, correlations between front traffic and closing ratios in skincare and fashion were negative; closing ratios tended to be systematically *lower* than average at high footfall outlets but a little higher than expected at quieter locations. Behaviour at fast food stores did not conform to this pattern.

The store entry ratio reflects a Double Jeopardy characteristic. While broadly constant between competing brands, an above average store entry ratio for brand leaders is a footfall density premium. Market leaders in each category also had more stores and had been established earlier, suggesting a link to the explanatory theory that underpins the Law of Natural Monopoly and Double Jeopardy (Ehrenberg et al., 1990). The former suggests that the biggest brands “monopolise” the many light category buyers, being the most familiar and the most easily available, while smaller brands attract slightly more of the heavier (and hence more experienced) category buyers. A higher than expected closing ratio for smaller brands (lower browsing, more purchasing) may reflect a slight preponderance of less risk-averse shoppers with wider brand repertoires in fashion and body care, but the in store Natural Monopoly effect is masked in fast food because the purchase decision timing appears to have been made more regularly before store entry. The presence of these familiar patterns in categories known to be constrained by DJ offers a response to the third research question, adding explanatory theory to the new EG in a way that can contribute managerial insight.

*4.4 A simple mathematical model for description and prediction*

The category constant can be used to predict mean hourly customer numbers from observed front traffic counts, simply multiplying one by the other. Table 4 demonstrates how it captures category performance closely with overall deviations between theoretical (T) and observed (O) values within five percentage points. Predictions for individual store brands then show some variance against the expected level for the category, highlighting where performance is rather better or worse than might be expected. For example, we see that fashion Brand A has only two thirds of its expected buyer numbers, while body care Brand B has almost double. The biggest variance is the underperformance of body care Brand C, which has less than half of its expected customers.

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Table 4 About Here

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For fashion Brand A the existence of the EG suggests that there is a strong possibility to improve returns per square foot at branches of this store. The model indicates how, and by how much. This type of analysis would not be possible from the like-for-like sales numbers normally used by most retailers, but here, in comparison with its competitive set, the new empirical generalization reveals that despite its superior footfall, Fashion Brand A is underperforming its category. Referring back to Table 2 we see that the problem is not with the closing ratio, which is as expected, but with the store entry ratio. Knowing this, and confident in its closing ratio effectiveness, further investment in shopper attraction is indicated in order to deliver higher sales, particularly in light of the challenge it faces from Brand B, with similar brand share but an attraction ratio a little *ahead* of expectation.

Body care Brand B appears to be compensating for cheaper, lower footfall locations with higher than expected conversion ratios. Further brand-level research would identify the cost effectiveness and relative ROI from this trade-off strategy between lower rental/lower front traffic and any higher payroll costs associated with higher sales incentives or simply higher staffing at busier times. The biggest variance in the table is however for body care Brand C. Reference to Table 1 confers some reliability on this finding and may reflect a systemic brand problem. Market share and store numbers are closely related in the category. Brand B has about one third the share and one third of the stores of Brand A; Brand C has about two thirds of the stores of B and yet achieves only half its share. The EG analysis provides some insight into this demonstrating how the brand is underperforming on both conversion ratios.

 5. **Discussion and Conclusions**

The aim of the study was to establish, test and model a generalisable relationship between front traffic and retail sales. Observations of consumer response were conducted between competing brands in smaller comparison goods retail and in fast food.The EG demonstrates that passing trade is by and large exactly what it says it is – mostly passing by. In fixed hourly observations almost a million people were counted walking by 40 storefronts of 12 retail brands. A high proportion was likely to have included category users and many were brand buyers yet just 20,000 purchases were observed in total – each hour just about two in every hundred became a customer. The consistency in the conversion ratios means that despite the low conversion rates front traffic is by far the dominant measure in eventual customer numbers. The regularity of that relationship across locations, days, footfall levels and brands is to the best of our knowledge a novel finding.

We found that the EG generalised and reflected a Double Jeopardy and Natural Monopoly characteristic. Comparing like for like outlets, smaller brands attracted fewer visitors than average, but converted slightly more of those shoppers than expected. In the market, brand share depends on total retail space as well as the quality of the locations, but our findings also suggested that market leaders may be reaping a double benefit from their ability to site stores in far busier locations where there appears to be a footfall conversion premium.

The systematic closing ratio observed across competing brands reflected the Double Jeopardy assumptions. While observations were not designed to capture switching, the consistency in the closing ratios suggests that shoppers in Brand B appear to like B as much as shoppers in Brand A appear to like A. Some exceptions were revealed, so that effective shopper marketing (or its opposite) can deliver variance from expected performance, but the EG broadly suggests that no retail brand is being bought much differently by its buyers than any other. The defining feature of retail performance is that some brands have *more buyers* than others and at the store level that is largely a function of the front traffic at that location.

Finally, the EG was shown to describe a law-like and “normal” retail performance and closely predicted an expected result for a given footfall in a named category. It therefore has scope, precision, parsimony, usefulness and links to theory, and is easy to apply, fitting Barwise’ requirements for a good Empirical Generalisation.

*5.1 Four Managerial Implications*

The study makes four contributions to retail marketing knowledge. First, the empirical generalisation offers management more precise information about critical location questions. Knowing that there is a broadly fixed relationship between footfall density and sales provides a much-needed key to the decision as Brown (1994) and Wood & Browne (2007) called for. Table 4 implies that given a little prior knowledge, managers can determine likely sales at any location from just a few hours of footfall observation with reasonable accuracy. In Appendix B we demonstrate at individual store level how close this can be. With this knowledge, front traffic metrics can provide a lever with which to negotiate initial rental and subsequent rent reviews.

Second, the benchmarks can be used to evaluate competitive performance on the double conversion dimensions of store entry and closing ratios. This adds greater management insight than anything derived from simple year on year sales data because as Lam *et al.,* (2001) suggest it provides a framework to diagnose specific areas for marketing intervention. Further however, for retail strategists the EG also benchmarks the relative performance of any *competing* retailer. It might therefore highlight areas of service performance that could be leveraged into a core competence and managed for competitive advantage (as for example body care Brand B appears to be doing, by trading in quieter locations but consistently converting slightly above prediction).

Third, the ratios have identified systematic variances in category buying propensities, reflected in the category constant. In combination with some idea of average spend this would help potential franchisees or other investors to assess the strengths and weaknesses of rival business opportunities, fast food versus skincare for example, on the basis that one attracts and/or converts shoppers more easily than another. Front traffic counts would then quickly provide a turnover estimate to set against initial investment costs and gross margins as part of the usual business analysis for any given site.

Last, but perhaps most important, these findings could be taken to suggest that nothing matters much beyond footfall, that given a busy enough location, predictable turnover must inevitably follow regardless of window display, merchandising, retail ambience, service levels, range, and so on; but this would be to miss the point. The retailers we observed are established, often global brands, surviving in fiercely competitive retail environment, just as others have not. They are therefore among the best retailers, for whom these EGs suggest a “normal” footfall conversion rate that is *already,* and must continue to be, met. Creative, motivating retail marketing initiatives are necessary just to maintain those conversion rates, running hard to stand still, yet despite the observed brands being highly differentiated, we found little if any evidence for a superior performance on either conversion or closing ratios that would suggest a niche performance, and much to support the Double Jeopardy assumptions of independence in purchase incidence and brand choice.

The DJ assumptions suggest that there is little advantage to be gained by targeting particular buyer groups. While the research did not explicitly examine buyer characteristics by brand, the new EGs confirm what most retailers must probably already know: it takes a lot of footfall to provide a viable level of passing trade. It is therefore more important to entice every category shopper by being as widely mentally and physically available as possible (Sharp, 2010; Romaniuk & Sharp, 2016) rather than limiting the chances of a sale by segmenting front traffic. Bogomolova *et al.,* (2016) show that category shoppers may be segmented socio-demographically by their shopping efficiency, but as Sharp (2010), Kennedy & Ehrenberg (2001), Wrigley and Dunn (1984) and Uncles and Kwok (2008; 2009) all demonstrate, heavy and light buying is distributed in much the same way across competing brands or store types. That evidence already shows that competing retailers share available category buyers predictably, in line with brand size; the new EGs may now predict how much is a fair share.

*5.2 Further Research*

These studies have produced promising findings, which suggest that only a quick and simple footfall observation is required to evaluate or support fundamental management decisions for any retailer in a given category. A rigorous programme of systematic scientific replication is now indicated, particularly as mechanical counting methodologies improve and give access to greater volumes of data. In particular it will be important to validate the observed closing data with retailer sales records where possible. Further replications are required in the same categories to improve the reliability of the relationship in further periods, different days of the week, and in other locations, and the work should be extended to discover how results generalise in the same categories but in different countries. Differentiated replications are also needed in many more categories, controlling for retail space as well as for location, to explore the inter-category variance in the ratios found here. Finally, the EG could usefully be tested between further location types with even wider variation in footfall densities, in other countries with further cultural variation in shopping behaviour, and across a wider range of competing retail brands.

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**Conflicts of interest**

None

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**Appendix A**

**Evaluating Face Validity: Published *vs.* Observed Footfall Counts**

|  |  |  |  |
| --- | --- | --- | --- |
| **Location** | **Country** | **Published Footfall Estimates** | **Count** |
|   |   | Year | Annual | Daily | Wk./Hr |
|   |   |   | *Millions* | *Thousands* | *Thousands* |
|  |  |  |  |  |  |
| Oxford Street (East) | UK | 2012 | 30.6 | 84 | 4.6 |
| Regent Street, London | UK | 2017 | 26.0 | 75 | 2.1 |
| Westfield Stratford | UK | 2015 | 25.3 | 69 | 2.0 |
| Dubai Marina Mall | UAE | 2016 | 16.0 | 44 | 3.3 |
| Emporium Lahore | Pakistan | 2014 | 16.0 | 44 | 1.9 |
| Dolmen Karachi | Pakistan | 2016 | 14.6 | 40 | 2.1 |
| Brent Cross, London | UK | 2015 | 12.4 | 34 | 1.0 |
| Centaurus Islamabad | Pakistan | 2016 | 11.0 | 30 | 1.2 |
| City Centre Ajman | UAE | 2016 | 10.5 | 29 | 1.3 |
| Kings Road, London | UK | 2016 | 9.6 | 26 | 0.9 |
| **Average** |  |  | **17** | **48** | **2.0** |
| ***Sources:*** | *Correlation between published estimates and observations: r =* | *0.74* |
| https://www.gva.co.uk/.../Evaluating-Future-Retail-Opportunities-in-the-St-Giles-Area |
| https://heartoflondonbid.london/wp-content/uploads/2017/08/WeeklyFootfall\_StJamessPiccadilly\_Wk30Yr2017\_L4L.pdf |
| http://westfield.completelyretail.co.uk/all-schemes/scheme/Westfield-Stratford-City-London.html |
| https://www.emaar.com/en/Images/Q1%202016%20Results%20-%2031%20Mar%202016\_tcm223-96911.pdf |
| Dawn.com |
| http://epaper.brecorder.com/2016/07/27/2-page/779433-news.html |
| https://www.hammerson.com/property/shopping-centres/brent-cross/ |
| http://epaper.brecorder.com/2016/07/27/2-page/779433-news.html |
| http://www.majidalfuttaim.com/our-businesses/properties/shopping-malls/city-centre/city-centre-ajman |
| https://media.realla.co/uploads/property/brochures/original/VK2Y9vrxiDHKvj1JLw1N-Q |  |

In order to establish face validity for the hourly footfall records collected in this study, results were compared against available published data. These commercial counts had been established in a number of ways including the use of sensors or cameras and sometimes by estimating from short manual counts.

The table reflects a reasonably strong correlation (*r* = 0.74) between published data and the hourly weekday counts reported in this study.

Published data represents total footfall at each location, not visitors to a particular floor of a mall or passing on each side of a street, and in addition cannot reflect variances due to seasonality, weather or hour of day. The important point is however that values reflect the study results in rank and order of magnitude by location.

**Appendix B. Applying the Empirical Generalisation to Store Level Data**

The tables below demonstrate four applications of the EG at the individual store level. In the fashion category, the ratios are applied to the sales performance of outlets in Marina Mall and then below, in the City Centre, summarising several hours for each.

In Fast Food a single hour’s trade is reported for each store: Tuesday in the Mall outlets and Wednesday in the High Street. Column averages are compared with the benchmarks developed. Hour by hour, individual store variances are clear, particularly in store entry ratios, but it can be seen that the category norms remain broadly close to their benchmark, even though the DJ patterns become obscured.

Store-level variances in one hour’s trade probably reflect simple stochastic timing effects or confounding influences at individual locations, yet the principle holds that with just a few hours of observation, enough data is gathered to reveal the benchmarks to predict expected sales at an individual location.

|  |  |  |
| --- | --- | --- |
| **Fashion in the UAE** |  | **Fast Food in Pakistan** |
|  |  |  |  |  |  |  |  |  |  |  |  |
| Saturday October 8th 2016  |  | Tuesday October17th 2016 |
| **Marina Mall:** Mean Values 4 Observations |  | **Mall Locations** 4pm to 5pm |
| (10 am; 11 am; 3 pm; 4 pm) |  |  |  |  |  |  |
|  | **Front Traffic** | **Store Entry** | **Conv Ratio** | **Buyers** | **Closing Ratio** |  | **Front Traffic** | **Store Entry** | **Conv. Ratio** | **Diners** | **Closing Ratio** |
|   |   |   | *%* |  | *%* |  |   |   | *%* |  | *%* |
| Brand A | 7378 | 552 | 5.7 | 237 | 50 |  | 1490 | 61 | 4.1 | 44 | 72 |
| Brand B | 5275 | 410 | 6.4 | 179 | 51 |  | 1505 | 47 | 3.1 | 32 | 69 |
| Brand C | 3866 | 352 | 7.2 | 148 | 50 |  | 1365 | 53 | 3.9 | 50 | 95 |
| Brand D | 3400 | 256 | 5.7 | 110 | 50 |  | 1305 | 47 | 3.3 | 39 | 82 |
| **Average** | **4980** | **392** | **6.3** | **168** | **50** |  | **1416** | **52** | **3.6** | **41** | **80** |
| **B/mark** |   |   | **5.8** |  | **47** |  |   |   | **3.7** |  | **81** |
|  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |
| Tuesday October 4th 2016 |  | Wednesday October 18th 2016 |
| **City Centre Locations:** Mean Values 3 Observations  |  | **High Street Locations**: 4pm to 5 pm |
| (9 am; 12 Midday; 4 pm) |  |  |
|   | **Front Traffic** | **Store Entry** | **Conv.Ratio** | **Buyers** | **Closing Ratio** |  | **Front Traffic** | **Store Entry** | **Conv. Ratio** | **Diners** | **Closing Ratio** |
|  |  |  | *%* |  | *%* |  |   |   | *%* |  | *%* |
| Brand A | 2553 | 152 | 4.6 | 61 | 60 |  | 2855 | 106 | 3.7 | 96 | 91 |
| Brand B | 1748 | 149 | 6.6 | 60 | 60 |  | 1565 | 89 | 5.7 | 66 | 74 |
| Brand C | 1560 | 129 | 6.9 | 52 | 60 |  | 945 | 29 | 3.0 | 23 | 79 |
| Brand D | 949 | 55 | 4.6 | 22 | 26 |  | 2698 | 60 | 2.2 | 46 | 77 |
| **Average** | **1702** | **121** | **5.7** | **49** | **52** |  | **2016** | **71** | **3.7** | **58** | **80** |
| **B/mark** |  |  | **5.8** |  | **47** |  |  |  | **3.7** |  | **81** |

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**Table 1: Brand Shares and Market Position**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|   | National Brand Share % | Number of Stores | Year of MarketEntry | Positioning |
| **Body care (UK)** |   |   |   |   |
|  Brand A | 1.0 | 311 | 1976 | Sustainable, Ethical |
|  Brand B | 0.4 | 101 | 1994 | Fun, Colourful, Fragrant |
|  Brand C | 0.2 | 62 | 1996 | Provence / lavender |
|  Brand D | N/a | 15 | 2010 | New York sophisticated |
|  |  |  |  |  |
| **Fashion (UAE)** |  |  |  |  |
|  Brand A | 3.2 | 33 | 1993 | Fast Fashion (brands) |
|  Brand B | 3.0 | 30 | 2004 | Value Fashion (PL) |
|  Brand C | <1 | 19 | 2005 | House of Brands |
|  Brand D | <1 | 9 | 2010 | Family  |
|  |  |  |  |  |
| **Fast Food (Pakistan)** |  |  |  |  |
|  Brand A | 30 | 69 | 1999 | Fried Chicken |
|  Brand B | 15 | 32 | 1998 | Deli Sandwiches |
|  Brand C | <5 | 12 | 2009 | Charbroiled Burgers |
|  Brand D | <1 | 9 | 1988 | Traditional Asian Grill |
|   |   |   |   |   |
| Sources: Value shares from Mintel. Beauty Retailing-UK-January 2017. Euro monitor, Apparel & Footwear, UAE 2015. Industry Sources  |

**Table 2: The Empirical Generalisation in Three Contexts**

|  |  |  |  |
| --- | --- | --- | --- |
|   | **Front Traffic** | **Store Entry Ratio** | **Closing Ratio** |
|  | *,000's /hour* | *% entering* | *% buying* |
|   | **Week** | **W/end** | **Week** | **W/end** | **Week** | **W/end** |
| **Body care (London)** |  |  |  |  |  |
| Brand A | 2.0 | 4.2 | 5.9 | 4.3 | 39 | 33 |
| Brand B | 1.0 | 1.8 | 4.1 | 5.9 | 61 | 48 |
| Brand C | 1.2 | 2.1 | 2.5 | 2.6 | 19 | 31 |
| Brand D | 0.7 | 1.2 | 2.7 | 2.5 | 55 | 56 |
| Mean Hourly Values n = 57,000 | **1.2** | **2.3** | **3.8** | **3.8** | **43** | **42** |
| **Fashion (UAE)** |  |  |  |  |  |  |
|  Brand A | 2.8 | 4.2 | 4.6 | 4.4 | 41 | 49 |
|  Brand B | 2.6 | 3.1 | 6.6 | 6.3 | 45 | 47 |
|  Brand C | 1.8 | 2.7 | 6.6 | 6.5 | 45 | 47 |
|  Brand D | 1.5 | 2.2 | 5.9 | 6.0 | 49 | 47 |
| Mean Hourly Values n = 720,000 | **2.2** | **3.1** | **5.9** | **5.8** | **45** | **48** |
| **Fast Food (Pakistan)** |  |  |  |  |  |  |
|  Brand A | 2.6 | 3.8 | 4.3 | 4.0 | 81 | 83 |
|  Brand B | 2.1 | 3.4 | 3.7 | 3.0 | 85 | 84 |
|  Brand C | 1.8 | 3.2 | 3.6 | 3.9 | 82 | 78 |
|  Brand D | 1.6 | 2.6 | 3.8 | 3.3 | 80 | 73 |
| Mean Hourly Values n = 124,000 | **2.0** | **3.3** | **3.9** | **3.6** | **82** | **79** |
|   | **1.8** | **2.9** | **4.5** | **4.4** | **57** | **57** |

**Table 3: Double Jeopardy & Natural Monopoly**

|  |  |  |
| --- | --- | --- |
| **Category, Brand & Location** | **Mean hourly…** |  |
| **Front** **Traffic** | **Entry Ratio** | **Closing Ratio** | **Category Constant** |
| **000,s** | **%** | **%** |  |
| **Body care (London)** |   |   |   |   |
|  Brand A | 3.1 | 5.1 | 36 |  |
|  Brand B | 1.4 | 5.0 | 55 |  |
|  Brand C | 1.7 | 2.6 | 25 |  |
|  Brand D | 1.0 | 2.6 | 56 |  |
| Mean Hourly Values n = 57,000 | 1.8 | 3.8 | 43 | 1.62 |
| *Correlation with footfall* | *0.61* | *-0.52* |  |
| **Fashion (UAE)** |  |  |  |  |
|  Brand A | 3.5 | 4.5 | 45 |  |
|  Brand B | 2.9 | 6.5 | 46 |  |
|  Brand C | 2.3 | 6.6 | 46 |  |
|  Brand D | 1.9 | 6.0 | 48 |  |
| Mean Hourly Values n = 720,000 | 2.7 | 5.9 | 47 | 2.72 |
| *Correlation with footfall* | *0.70* | *-0.89* |  |
| **Fast Food (Pakistan)** |  |  |  |  |
|  Brand A | 3.2 | 4.1 | 82 |  |
|  Brand B | 2.8 | 3.4 | 85 |  |
|  Brand C | 2.5 | 3.7 | 80 |  |
|  Brand D | 2.1 | 3.6 | 77 |  |
| Mean Hourly Values n = 124,000 | 2.6 | 3.7 | 81 | 2.99 |
| *Correlation with footfall* | *0.62* | *0.74* |  |
|   |   |   |   |   |

**Table 4: Predicting and Evaluating Performance from Front Traffic**

|  |  |  |  |
| --- | --- | --- | --- |
| **Category, Brand and Location** |  | **Customers/Hour** |  |
| **Observed Front Traffic** | **Observed** | **Theoretical** | **Deviation** |
| **(Mean/hour)** | **O** | **T** | **(O-T/O)** |
| **Body care (London)** |   |   |   |   |
|  Brand A | 3100 | 57 | 50 | 13% |
|  Brand B | 1400 | 38 | 22 | 41% |
|  Brand C | 1700 | 11 | 26 | -151% |
|  Brand D | 1000 | 14 | 15 | -11% |
|  |  |  |  |  |
| Total |  | 119 | 114 | 5% |
|  |  |  |  |  |
| **Fashion (UAE)** |  |  |  |  |
|  Brand A | 3500 | 71 | 95 | -34% |
|  Brand B | 2900 | 85 | 78 | 8% |
|  Brand C | 2300 | 68 | 61 | 10% |
|  Brand D | 1900 | 53 | 50 | 5% |
|  |  |  |  |  |
| Total |  | 276 | 284 | -3% |
|  |  |  |  |  |
| **Fast Food (Pakistan)** |  |  |  |  |
|  Brand A | 3200 | 202 | 178 | 12% |
|  Brand B | 2750 | 147 | 154 | -5% |
|  Brand C | 2500 | 144 | 145 | 0% |
|  Brand D | 2100 | 112 | 123 | -9% |
|  |  |  |  |  |
| Total |  | 605 | 600 | 1% |
|   |   |   |   |   |