Multiple Price Posting and Consumer Search Obfuscation: Evidence from an Online Market

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Abstract

This paper examines the use of multiple brands to investigate if this practice is consistent with consumer search obfuscation. This is for the UK online motor insurance market, where 83 brands are owned by 37 firms, of which 16 are multi-brand firms. Price ranking data are analysed for multiple and single-brand firms at a sub-market level by individual and car type. Overall, while firms price discriminate by heavily advertising a single brand, the paper finds that multi-brand firms cluster their prices and post significantly lower prices. It is consistent with search obfuscation, but as firms engage in other pricing strategies, it is most apparent for firms that post prices for a relatively large number of brands.

Key words: Search obfuscation, multiple price posting, online markets, price comparison websites, price discrimination, motor insurance.

JEL Classification codes: L11, D83 L81 and G22.

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1. Introduction

An intriguing feature of online markets is the ease with which sellers can post multiple prices using different brand names. With only a relatively modest outlay to create a website a firm can enter a new brand into the market, while due to the widespread use of price comparison websites the cost of reaching consumers is low. It gives a firm the opportunity to obfuscate consumer search, since by posting prices for multiple brands the firm can not only reduce the effectiveness of search (a consumer may unwittingly compare prices for brands that are from the same firm), but it can increase the consumer ignorance of its competitors' prices (Ireland, 2007). There is a large literature on search obfuscation in online markets (Ellison and Ellison, 2009; Wilson, 2010), but this is mainly theoretical in nature, so that there is little empirical evidence for the practice of search obfuscation.

The purpose of this paper is to analyse empirically the use of multiple brands by firms in an online market to investigate if this practice is consistent with search obfuscation. This is for the UK online motor insurance market, where it is common for firms to offer insurance using multiple brand names. As insurance is a broadly homogeneous good, then this market has several advantages. First, sub-markets can be identified by individual and car type, which means that within sub-market those factors that are common to brands are held constant, such as pricing to discriminate by risk or type. Second, online motor insurance does not have attributes that clearly defines 'distance', either in the intrinsic characteristics of the good or in the physical location of sellers. This means it is difficult to construct a motive for brand proliferation based on entry deterrence (Schmalensee, 1978).[1]

Of course, firms may still advertise their brands, which at the sub-market level may be an attempt to discriminate on unobserved consumer characteristics, such as income or tastes. McDonald and Wren (2012) find that advertising in the online motor insurance market is primarily informative in nature, while as motor insurance price quotes are both individual and

[1] Motor insurance may fit some of Schmalensee's assumptions, but key to entry deterrence in this model is some 'distance' between identifiable attributes of the product, which leads to localized rivalry. These attributes are not obvious in motor insurance, while advertising in this market is primarily concerned with name recognition. Multi-brand firm hide the firm identity of their brands, which suggests they are not seeking to deter entry.

car specific, consumers cannot discover prices from adverts, so that advertising campaigns in this market typically focus on the existence of a brand or its general cheapness, rather than on brand loyalty. Nevertheless, we find that the multi-brand firms advertise more heavily than single-brand firms, and that they tend to concentrate this advertising on a single brand, which suggests that they also engage in persuasive advertising. However, whereas persuasive advertising suggests prices will be relatively higher and more dispersed, search obfuscation implies that firms will cluster their prices and towards the lower end of the price distribution, where they are more likely to be discovered by consumers.

The price data are collected for different individual types, by age, occupation and sex, and for five car types, giving 110 motor insurance sub-markets. Further, these are collected at four dates giving 28,327 observations on brand prices across 440 price sets. The individual and car type characteristics are chosen to be representative of the motor insurance market. In total, 83 motor insurance brands are identified, which are owned by 37 firms, of which 16 are multi-brand firms that offer 62 brands. Multi-brand firms tend to quote in each sub-market, but not always with all of their brands. Allowing for this, and for other strategic behaviour of the firms, such as advertising, we find that multi-brand firms tend to cluster their prices in a sub-market and post these towards the lower end of the distribution of sub-market prices. It is consistent with search obfuscation. While all multi-brand firms are found to cluster prices, this is most apparent for firms that post prices for a relatively large number of brands.

In the next section the literature is discussed and the hypotheses are formed. Section 3 analyses the sub-market distribution of prices using price rankings. The main empirical work is carried in section 4, where the results are presented, and section 5 concludes

2. Background and Hypotheses

While firms may seek to obfuscate search in conventional markets, interest in this strategy has recently increased as consumers have lower search costs in online markets, while the opportunities to obfuscate are greater. Ellison and Ellison (2009) identify two ways in which a firm can obfuscate consumer search. First, using product add-ons that are unobserved by searching consumers, but which lead to a higher price at purchase (Ellison, 2005; Gabaix and Laibson, 2006). Second, by making it more time-consuming for a consumer to locate a product or discover its price and hence increasing the consumer search cost (Ellison and Wolitzky, 2009; Wilson, 2010). This paper considers multiple-price posting, which is a form of search obfuscation, as it gives rise to incomplete search by consumers. To our knowledge, the only paper that formally analyses this form of search obfuscation is Ireland (2007).

In the model of Ireland (2007) firms offer multiple prices, but consumers are unaware that prices may originate from the same firm. The consumers search non-sequentially at an *ex ante* fixed sample size that differs between consumers, so that a proportion θ randomly sample one price and (1 - θ) randomly sample two prices. Given n ($\geq$ 2) market prices, if a firm offers two prices, p_a and p_b: each price sells to θ / n consumers sampling one price; to $\frac{2(1-\theta)(n-2)}{n(n-1)}$ consumers sampling two prices and observing only one of p_a or p_b; but to $\frac{2(1-\theta)}{n(n-1)}$ consumers sampling two prices and observing both prices.[2] This latter group means the firm can capture all of the consumers that observe its two prices only, and since any discount on a price loses it revenue then optimally it sets $p_a = p_b$, so that the prices are clustered.

Of course, in relation to the Internet, a comparison website / shop-bot may act as a clearinghouse in which consumers discover all prices simultaneously. This is different to the non-sequential search assumed by of Ireland (2007), although his result still has relevance to this market setting. Dulleck *et al*., (2011) find that consumers at price comparison websites perform a two-stage decision-making process: in the first stage, they short-list firms by price; and in the second stage, they evaluate the short-list according to other characteristics. This is consistent with other studies using price comparison website data, which find sales decline sharply for firms that are not ranked in the lowest few prices (e.g. Baye *et al*., 2009; Ellison and Ellison, 2009; and Brynolfsson *et al*., 2010). Thus, Internet search using a comparison website may still resemble a non-sequential search process.

Given this, then two hypotheses can be formed as follows about the pricing strategy of a firm that seeks to obfuscate search by posting multiple prices under different brands:

<u>Hypotheses</u>: *A firm posting multiple prices under different brand names obfuscates consumer search if it*: H1: *clusters its prices*; *and* H2: *posts relatively lower prices*.

Hypothesis H1 follows from Ireland (2007). Given that a consumer initially selects a set of brands at a similar price, and then conducts further search on these, the clustering of prices is consistent with multiple-price posting for the purpose of search obfuscation. As a necessary condition, the firm's prices must be shortlisted by a consumer, so that Hypothesis H2 is that the prices are set towards the lower end of the distribution of prices. Any evidence for these

[2] These sum to 2 / n, so that the firm gets the whole market when n = 2.

hypotheses is unlikely to be consistent with other explanations, as price discrimination within a sub-market is likely to lead to higher prices, which may result in more dispersed prices.

3. The Data

The price data were collected manually from the leading UK motor insurance comparison website, *confused.com*.[3] Motor insurance quotes depend on driver-associated risk, for which the price comparison site requires certain individual characteristics to be specified, including the age, occupation and sex. It is advantageous, as these characteristics can be hold constant. Taking-on assumed identities data were collected for four ages (25, 40, 55 and 70 years), four occupations (blue-collar, white-collar, unemployed and retired) and males and females. For realism, not all ages and occupations are matched, so that retirees are aged 55 or 70 years only, while 70-year-olds are retired only, giving twenty-two individual types. The car type is held constant, so the data were collected for five cars, which gives 110 distinct *sub-markets*.[4] Overall, these provide are a good representation of the motor insurance market.

The price data were collected in 2011 on four occasions, at approximately six-weekly intervals, from January to July, so that there are 440 *price sets*. The data were collected over a weekend in each case to minimise any effect of updating of the companies' prices. In total there are 28,327 observations on prices, which is an average of about 64 quotes per price set. The motor insurance policies vary in other details, so that in collecting these data these were specified to keep as many as possible of these constant, reflecting average market conditions: a fully comprehensive level of cover, an annual mileage of 9,000 miles, cover for a business, commuting and social use and a 5-years no-claim bonus. The insurance policies also differ in other features that may sometimes be included as non-standard, such as cover for a courtesy car, legal fees, breakdowns or windscreen damage. Since these are specified upfront with the quoted price on the websites then they probably reflect product differentiation rather than search obfuscation from product add-ons (Ellison, 2005). Either way, details of these non-standard features were recorded, and these are used as controls in the regression analysis.

[3] Consumers enter their policy details at *confused.com*, which visits the websites of all quoted insurers. Offered prices are then reported to the consumer, ranked from lowest to highest, along with some policy details and brand information. The comparison site *confused.com* generates its revenue from sales generated from click-through or telesales made using a *confused.com* reference number. Similar data, for earlier years, are used by the authors to examine other aspects of online search, including between search ability and price dispersion and between price and advertising in the presence of heterogeneous search (McDonald and Wren, 2009, 2012).

[4] These are the Ford Fiesta Encore, Ford Focus Zetec, Vauxhall Vectra CD 16V, BMW 525i and Mazda MX-5. Each of these cars is a high-selling model in the respective market segment.

The Brands

Each brand quotes at most a single price in a price set, while in total 83 brands post a price in at least one of the 440 price sets. As a first step, it is necessary to determine the ownership of each brand. This is potentially easier for motor insurance than for other markets, where there are many small companies with opaque brand ownership, although this information tends to be well concealed on the motor insurance websites, with only one firm openly advertising the common ownership of its brands.[5] This appears to be deliberate, as the brands are also not transparently related to each other, either in name or website design. The concealment of ownership is consistent with search obfuscation, and in Ireland (2007) the consumers are unaware that prices (i.e. brands) arise from the same firm. However, it is also consistent with other explanations, such as price discrimination, where firms seek brand distinctiveness (Wolinsky, 1987).

The firm ownership of the brands was determined by consulting industry publications, parent company websites, annual reports and Internet search. The 83 brands on *confused.com* are owned by 37 firms, of which 62 brands are owned by 16 multi-brand firms and the other 21 brands have separate ownership. Table 1 shows the characteristics of the 16 multi-brand firms. Around half the multi-brand firms have two or three brands, and the other firms have up to six brands, with the exception of the BGL Group, which has twelve brands. The BGL Group is an insurance broker that offers insurance through its own brands and also in the names of firms with which it has "affinity deals". The two firms that have six brands, Ageas and BDML, also have affinity deals with non-specialists.[6] These affinity deals are with well-known branded firms that are non-insurance specialists, such as the HSBC bank and Post Office mail service. The affinity deals are increasingly important in the UK motor insurance market, and in other product areas, as firms with no experience of insurance seek to exploit their brand. An affinity deal typically involves the insurance specialist providing the pricing strategy, but also an underwriting panel of insurers, policy administration and marketing.

[5] This is the MMA Group. Several firms post prices for brands that are related to one another, but differentiated (e.g. the Hastings company offers insurance as Hastings Direct, Hastings Premier and Hastings Essential, where Hastings Premier includes many policy add-ons as standard, such as a courtesy car, while Hastings Essential is basic). As we seek to control for product add-ons, we drop the differentiated brands from the sample, but retain the brand that has features closest to the market standard (i.e. Hastings Direct).

[6] BGL Group has affinity deals with nine non-insurance specialists (HSBC, Post Office, Auto Trader, Bradford and Bingley, Halifax, Lloyds TSB, Marks and Spencer, RAC and Yes Insurance), Ageas has two affinity deals (Kwik-Fit and John Lewis) and BDML has three (Asda, Virgin and Debenhams). No other firm has these deals.

[table 1 here]

The second column of table 1 shows that nearly all multi-brand firms post at least one price in all or virtually all price sets, although two firms, AXA and Esure, are selective as they do not quote for more risky drivers, such as the unemployed, which is shown in Appendix table 1. Of the price sets in which a multi-brand firm quotes, the third column of table 1 shows that many firms choose not to post all their prices. This could be for strategic reasons (e.g. two of the brands of Fresh are mutually exclusive across sub-markets), because firms do not quote for more risky individuals, including 25-year olds and males (Appendix table 1), or due to entry.[7] The fourth column of table 1 shows that for the price sets in which a multi-brand firm quotes there is a positive and reasonably strong correlation between the number of brands that a firm owns and the number of brands that it quotes in these price sets on average (r = 0.40).

The last two columns of table 1 examine the advertising of the multi-brand firms, with data for 2010. On average, the multi-brand firms spend much more on advertising than the single-brand firms (£3.8m and £1.8m respectively), although varying from zero to £17.5m. However, there is a weak relationship between advertising and the number of brands for the multi-brand firms (r = -0.08, but r = -0.07 if BGL Group is excluded), and indeed some of the multi-brand firms that advertise most heavily have just two brands. The mean advertising expenditure per brand is virtually identical between the multi-brand and single-brand firms, but the final column of table 1 shows that the multi-brand firms spend 80% of this advertising on a single brand (i.e. £50.2m of £61.1m). This is an average of £3.1m, so that the other 46 brands of the multi-brand firms are relatively little advertised. In fact, only three firms spend more than £1m on brands other than their most-heavily-advertised brand, of which one, RBS, still spent 92% of its advertising on its leading brand. It indicates that the branding activities of the multi-brand firms tend to be concentrated on a single leading brand.

4. Multi-Firm Brand Prices

The mean and coefficient of variation of motor insurance prices (i.e. quoted premiums) are presented in table 2 across the price sets for each car type. There is no attempt to control for

[7] Ten brands entered the market after the date when data were first collected, while prices for two brands were not posted for at least one of the subsequent dates after when the data were first collected for the brand.

advertising in this table or for other factors affecting the price. For each type, the mean price tends to be lower for the multi-brand firms than for the single-brand firms (on average, 97% of the prices offered by single-brand firms), but which is much greater when only the lowest price offered by a multi-brand firm is considered (89%). Given that multi-brand firms tend to heavily advertise a single brand, which if it is persuasive advertising will increase the price, it offers some support for Hypothesis H2. When the coefficient of variation is considered, table 2 suggests that prices are more clustered for the multi-brand firms than for single-brand firms (and much more so for the lowest prices offered by the multi-brand firms). However, it is not the case for the Fiesta and Focus cars. These are mass-market car segments, and we find that some multi-brand firms that are selective in the way they use their brands post higher prices for these cars.[8] It suggests some heterogeneity in the firm's pricing strategies, but by itself it does not offer strong support for Hypothesis H1.

[table 2 here]

To formally analyse search obfuscation the price data are transformed into a ranking for each price set. This is appropriate as interest is in the firm's strategy relative to other firms in the same price set, while it helps hold constant differences in the level of prices in different sub-markets due to discrimination or risk. It assumes that the firms behave the same in each sub-market (e.g. identical risk preferences), for which we do not have data, although fixed effects are included in the regression analysis below. Comparison is made across sub-markets using the price ranking data. To construct price rankings, the data are transformed using the Hazen Rule, where the Hazen plotting position of firm *i* in a price set *j* is given by:

$$RANK_{ij} = \frac{(r_{ij} - 0.5)}{n_j}, \tag{1}$$

where r_{ij} is the firm's ranking in the price set *j* and n_j is the number of firms in *j*. A lower value of *RANK* indicates a lower price. The Hazen Rule is advantageous, as each firm within a price set has a plotting position between 0 and 1, while the median rank is equal to 0.5 with a symmetric distribution of rankings about this. Other rules exist for ranking the data, such as the Weibull and Percent Rank rules (Cox, 2005), but these have similar properties and give

[8] Inspection of the data, suggests that four firms tend to post higher prices for these models, AXA, Europa, RSA and Fresh, but these either post a small number of brands or post prices less frequently (table 1).

an identical ordinal ranking, while in cardinal terms the Hazen Rule lies between these.[9]

We begin by undertaking a statistical analysis of the brand price rankings. While it is based on unconditional rankings, it is informative about a multi-brand firm's pricing strategy. To investigate Hypothesis H1, the variance of the brand rankings in a price set for each multi-brand firm is compared to the variance in rankings for the price set as a whole. For a random sample, the expected value of the sample variance is equal to the population variance (Mood *et al*., 1974), so that the Null Hypothesis is that the variance of brand rankings for the multi-brand firm is the same as all firms. If this is rejected and the sample variance is lower then it offers support for search obfuscation under Hypothesis H1. However, if the Null cannot be rejected, then the firm may still search obfuscate through multi-brand pricing but also engage in other activities, such as persuasive advertising that raises the price on some brands.

Table 3 presents the mean sample variance for each multi-brand firm across the price sets in which it posts prices. Overall, across all 83 brands it shows that the mean population variance is 0.085, so that in all but three cases the mean sample variance is less than the mean population variance. One of these is very marginal, while of the other two, table 1 shows that Europa posts prices the lowest number of brands in any price set in which it quotes (i.e. 1.23), while Fresh never quotes in any price set with all of its three brands, so that each of these is adopting non-standard pricing strategy. The Null Hypothesis is examined using a statistical test based on paired observations but under a one-tailed t-test (Kazmier and Pohl, 1987). The results in table 3 show that the Null can be rejected for half of the multi-brand firms at the 5% level at least, and that in each case the sample variance is lower, offering support for H1. A similar result was found when comparison was made with the single-brand firms.[10] Hence, if anything, it suggests that the multi-brand firms tend to cluster their prices.

[table 3 here]

The clustering of prices is likely only to be effective if the multi-brand firms post low prices. To examine Hypothesis H2, the second column of table 3 shows the mean price ranking of each multi-brand firm. On average, the Hazen Rule implies a mean ranking of 0.5, but table 3 shows that only seven of the multi-brand firms have a mean price ranking of less than this. This does not offer support for Hypothesis H2, but again it may be that the multi-brand firms

[9] The Hazen Rule is a member of a family of plotting positions, given by $(r_{ij} - a) / (n_j - 2a + 1)$, for which $a = 0.5$. There is recommended by Cox (2005), although there is little guidance on the appropriate rule.

[10] In this case, the A&A Group also has a significantly lower variance, but at the 10% level.

also engage in persuasive advertising, for which evidence was found in tables 1 and 2.

Finally, as a further exploration of Hypothesis H1, i.e. price clustering, for each multi-brand firm the correlation coefficient is calculated for the price ranking of each pair of brands across price sets in which both brands are quoted. The mean correlation coefficient for each multi-brand firm for these pairwise comparisons is presented in the final column of table 3.[11] Overall, it reveals a similar pattern to the first column of table 3, as the firms that tend to have a high correlation also tend to have a significantly different (lower) variance in their rankings. For other multi-brand firms the correlations are generally positive. Of course, a firm's brands have similar underlying costs, so that a positive correlation is expected, but table 3 shows that some firms are setting prices at virtually identical price rankings for all their brands.

On the last point, comparison can be made with the correlation coefficients calculated for all 83 brands, for which there are a total of 3,403 pairwise comparisons. The distribution of coefficients is shown in figure 1a, which resembles a normal distribution. However, it has discernibly fatter tail on the right-hand side, which indicates that some pairs of brands have a strong positive correlation in their price rankings. What is interesting is that figure 1b, which plots the corresponding distribution for the multi-brand firms, shows that these firms account almost wholly for the strong positive correlations. Indeed, excluding the BGL Group, figure 1c shows that the multi-brand firm correlations are always positive. A Kolmogorov-Smirnov two-sample test shows that the multi-brand and all firm distributions differ at the 1% level.

[figures 1a, 1b and 1c here]

5. Regression Analysis

To examine search obfuscation the following equation is regressed across brands:

$$RANK_{ij} = \beta_0 + \beta_1 \, MULTIBRAND_{ij} + \beta_2 \, STRATEGY_{ij} + \delta_i + \delta_j + \varepsilon_{ij} \quad \text{and}$$

$$\varepsilon_{ij} \approx N(0, \sigma_{ij}^2), \text{ where } \sigma_{ij}^2 = \lambda_0 + \lambda_1 \, MULTIBRAND_{ij} + \lambda_2 \, STRATEGY_{ij} + v_{ij}. \qquad (2)$$

where *RANK* is the Hazen price ranking of brand *i* in price set *j*. To examine the hypotheses, both *RANK* and the variance of the normally distributed error term depend on the regressors.

[11] There are 139 of these comparisons, i.e. one correlation coefficient for firms with 2 brands, three for those with 3 brands and so on, all the way up to 66 pairwise comparisons for the 12 brands of the BGL Group.

MULTIBRAND is a dummy that is unity if the brand is owned by a multi-brand firm, but zero otherwise. If under Hypothesis H1 the multi-brand firms cluster their prices then we expect a smaller variance for these brands, such that $\lambda_1 < 0$, whereas if under Hypothesis H2 the multi-brand firms post lower prices then we should find lower price rankings, such that $\beta_1 < 0$. Equation (2) is regressed across all 28,327 observations on prices using maximum likelihood. The price ranking is a limited dependent variable, which can be transformed using the logistic function to constrain the predicted values of *RANK* to lie on the unit interval. The results for this are given below, but since they give virtually identical estimates in sign and significance, the analysis focuses on the untransformed data, which has greater intuitive appeal.

The above discussion suggests that firms may engage in pricing strategies other than search obfuscation, and a vector of terms, *STRATEGY*, is included to control for these, where summary statistics for these are given in table 4. It is possible to form *a priori* predictions on the effect of each of these *STRATEGY* terms on the price ranking, i.e. β_2 in equation (2), but similar predictions cannot always be made about the error variance, λ_2 in (2). This is because it depends on where in the distribution of price rankings the brands that are affected by each *STRATEGY* term are located. For example, if the affected brands have relatively low (or high) rankings then the variance is smaller, suggesting greater price clustering, but if the brands are drawn from across the distribution of price rankings then the variance may be greater.

[table 4 here]

First of all, *STRATEGY* includes a term for the logarithm of the brand advertising expenditure (*ADVERT*). Table 1 shows that the firms advertise their brands, and elsewhere it is found that advertising in this market tends to be informative in nature, with firms seeking greater brand recognition to attract searching consumers (McDonald and Wren, 2012). If this reduces the brand's demand elasticity, then the firm can increase its sales by posting a lower price, and a negative sign is expected on β_2. Since the firms will post these advertised brands towards the lower end of the price ranking distribution, where they are more likely to be discovered by consumers then it suggests price clustering, and a negative sign is expected on λ_2. Of course, at an Internet Shopbot, Smith and Brynolfsson (2001) find that consumers also place value on attributes such as branding, with table 1 revealing that the multi-brand firms concentrate their advertising on a single brand. It suggests that the multi-brand firms also engage in persuasive advertising, and to capture this effect *MULTIBRAND* is interacted with *ADVERT*, for which a positive sign is expected on β_2. As the firms heavily advertise a single leading brand then it suggests greater variance, so that a positive sign is expected on λ_2.

Second, it was found above that some of the brands for the three firms with the largest number of brands represent affinity deals with non-insurance specialists. The non-insurance specialists tend to be well-known firms that are heavily branded, and it is reasonable that this will carry over to the brands that are affinity deals. Further, even though the motor insurance firms set prices for the affinity brands, there are additional considerations, such as the return expected by a non-specialist, that mean it is less able to use these brands to search obfuscate. Given this, a dummy is included for affinity brands (*AFFINITY*), where we expect $\beta_2 > 0$.

Third, it was observed that the multi-brand firms do not always post all their brands in a price set (table 1). This may indicate that the firm is less concerned with search obfuscation and that it is pursuing some other pricing strategy, such as posting only some of its brands for low-risk consumers. To capture this, an index is included that measures the mean frequency with which a firm posts all its brands across the price sets:

$$POST = \frac{(\text{number of brands - mean number of posts per brand})}{\text{number of brands}}.$$

This lies on the unit interval, e.g. for Europa in table 1 it is (2 - 1.23 / 2) = 0.385. It is zero if a multi-brand firm post all its brands, and for single-brand firms. Again, we expect $\beta_2 > 0$.

Finally, the MMA Group openly declares the ownership of its brands. As this cannot be a search obfuscation strategy, for which the concealment of ownership is necessary, a term is included for these brands (*MMA GROUP*), for which once again we expect $\beta_2 > 0$.

In addition to these *STRATEGY* terms, a range of other controls are included that are measured at either the brand or price set level, i.e. δ_i and δ_j in (2).[12] The estimates on these terms are not reported below, although the sensitivity of the results to these is examined. The first term is for the firm market share, which is a proxy for the number of loyal consumers. A firm with more loyal consumers may be able to charge a higher price across it brands.[13] The brand market share is broadly similar for multi-brand and single-brand firms. Second, brands

[12] These are included in the body of the regression in (2) only, as when they also included on the error variance the maximum likelihood regression fails to achieve convergence, perhaps because they are not identified.
[13] Market share is available from Mintel (2011), but for the gross underwritten premium only. Since this may understate the sales of insurance brokers, who do not underwrite premiums, a dummy is included on this term for firms with a market share of less than 1%. For multi-brand firms, the correlation coefficient between the market share and number of brands is r = -0.09 (it is r = 0.08 excluding the BGL Group).

that give a higher level of consumer satisfaction may be able to charge a higher price, which is the so-called 'service premium'. A term for a consumer satisfaction index is included that is based on a survey of policyholders (Auto Express, 2012). It is available at the firm level, but also for many brands, so a dummy is included for missing cases at the brand level. Third, a dummy is included for insurance brokers, which may have lower costs than direct sellers. Fourth, product dummies are included to control for policy differences according to whether a policy includes a deductible / excess, courtesy car, and legal fee, breakdown or windscreen cover. Finally, price set dummies are included for each individual and car type, and for each date when the data were collected. The inclusion of firm dummies is considered below.

Regression Results

Equation (2) was regressed across all 28,327 observations using maximum likelihood, and the result is presented in column (1) of table 5. As regards the *STRATEGY* terms, these are each significant at the 1% level and the estimates on β_2 conform to prior expectations. They show that advertising has a negative effect on the price ranking, which suggests it is informative, but that for the multi-brand firms the interaction term is positive, which indicates that there is a persuasive element to the advertising of the heavily-advertised brands. While the net effect of advertising on the price ranking of these brands is not significantly different from zero, a higher price is set for the heavily-advertised brands than would otherwise be the case. This is consistent with the brand mark-up (Smith and Brynolfsson, 2001). The λ_2 estimates suggest informative advertising leads to greater price clustering, as firms post prices for these brands close to other brands where they are more likely to be discovered by consumers, whereas for persuasive advertising the higher prices lead to less clustering in the price rankings.

[table 5 here]

On the other *STRATEGY* terms, the β_2 are correctly signed, such that the affinity brands, the lower likelihood of posting a brand and the open declaration of brand ownership all lead to a higher price ranking in a sub-market. The estimates on the variance λ_2 indicate that affinity brands tend to have higher price rankings, leading to a lower variance and greater clustering (*AFFINITY*), but the firms that do not always post all their brands are drawn from across the distribution of price rankings, so there is less clustering (*POST*). Finally, the controls that are not shown in table 5 are plausible, including the market share and consumer satisfaction.[14]

Of course, interest is in the estimates on *MULTIBRAND*, and these are both negative and significant, providing support for Hypotheses H1 and H2. In particular, the λ_1 estimate supports H1, as it indicates that the prices of the multi-brand firms are less dispersed, so that they cluster their brands in a sub-market relative to all prices, while the β_1 estimate supports H2, as the multi-brand firms offer their brands at relatively lower prices in a sub-market. The magnitude of the effects is strong, as a multi-firm brand will reduce its price ranking by 0.25, where the median brand has a ranking of 0.5 on the [0, 1] plotting position. Further, the error variance is reduced by about 0.10, but across all firms the λ_0 estimate suggests it is 0.35.

The remainder of table 5 examines the robustness of these results. Column (2) omits the interaction term on advertising for the multi-brand firms (i.e. *ADVERT* MULTIBRAND*), but while the estimates on *MULTIBRAND* are smaller in magnitude, they are still significant at the 1% level, and have a negative effect on the price ranking and dispersion. Further, when both advertising terms are omitted in column (3) then there is a similar conclusion. Column (4) retains the advertising terms, but omits the other *STRATEGY* terms, but this leads to much the same conclusion. Finally, column (5) transforms *RANK* using the logistic function, which alters the magnitude of the coefficient estimates, but in their sign and significance these are virtually identical to those in column (1), lending weight to the central conclusion.

Several further tests were conducted. First, the estimates suggest that the multi-brand firms engage in persuasive advertising, but table 1 shows that they tend to do this by heavily-advertising a single brand. To explore this, equation (2) was re-estimated, but with a dummy on *ADVERT* for the most heavily-advertised brand of each multi-brand firm, which is in place of *ADVERT*MULTIBRAND*.[15] However, the result is much the same as that in column (1) of table 5, with negative and significant estimates on *MULTIBRAND*. Second, based on the raw data, table 2 finds that prices are more clustered for the multi-brand firms compared to single-brand firms, but that it is not the case for the mass-market Fiesta and Focus cars. To examine this, car dummies were placed on *MULTIBRAND*, and equation (2) re-estimated with these in spline form. While some significant differences exist between the car types, in each case the spline terms are significant at the 1% level, negative and similar in magnitude.[16]

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[14] These are both significant and have a positive effect on the price ranking, while the product dummies lead to higher price rankings, but except for windscreen cover. We also find that brokers set lower prices.

[15] For Europa, the A&A Group and Fresh, which do not advertise (table 1), we set this dummy equal to zero.

[16] For β_1 these range from -0.284 to -0.245 and for λ_1 from -0.115 to -0.085. There was no significant difference in λ_1 between the Vectra, BMW and MX-5 cars, but a significantly higher estimate for the Fiesta and Focus cars at the 5% level. This suggests that the prices for the mass-market cars are less clustered, which finds support in table 2, where an explanation can also be found.

Finally, equation (2) was re-estimated with slope dummies on *MULTIBRAND* for the number of brands posted by the multi-brand firms. The estimates of β_1 and λ_1 for the number of brands are shown in spline form in the first part of table 6. As a group, the *MULTIBRAND* terms differ significantly from each other at the 1% level for both β_1 and λ_1. Of interest, the estimate on λ_1 is significantly smaller for firms with 2 or 3 brands compared to firms that post a larger number of brands. Given that we control for advertising and other strategies of the multi-brand firms it is difficult to attribute this difference to some other pricing strategy of the firms. Rather it seems that search obfuscation is most apparent for firms with a relatively large number of brands, although it is still evident for those firms with 2 or 3 brands. The second part of table 6 shows that this practice is prevalent across the multi-brand firms. It re-estimates (2), with dummies on *MULTIBRAND* for each multi-brand firm. The estimates on λ_1 are always negative and significant, which is also generally the case for β_1, so that taken as a whole these results offer convincing evidence for the practice of search obfuscation in this online motor insurance market.

6. Conclusions

This paper uses data for the online UK motor insurance market to examine whether multiple-price posting by firms under different brand names is consistent with search obfuscation, by which firms may seek to limit the effectiveness of consumer search. The analysis is at a sub-market level that holds constant the car type and certain individual characteristics, although even at this level we find that firms engage in a range of strategies, such as informative and persuasive advertising, that have implications for brand prices. Controlling for these, we find that the multi-brand firms not only post lower prices, but that they cluster their prices, both of which are consistent with a search obfuscation strategy. This result is remarkably robust, and it occurs both for every car type and in the case of virtually every multi-brand firm. It is most evident for firms that offer more than several brands, possibly reflecting different motives for multiple-price posting by firms under different brand names. Overall, it indicates that search obfuscation is an important component of firms' online pricing strategies.

Table 1: Characteristics of Multi-Brand Firms

Firm	Number of Brands	Price Sets: In which Firm Quotes (%)	Price Sets: With All Brands* (%)	Price Sets: Mean Number of Brands*	Advertising Expenditure: Firm-level (£'m)	Advertising Expenditure: Leading Brand (%)
Europa	2	99.6	23.1	1.23	0	-
Zurich	2	99.8	36.9	1.37	0.10	100.0
Brightside	2	99.8	66.7	1.67	0.01	100.0
RSA	2	94.3	46.5	1.71	5.93	99.5
AXA	2	54.8	75.1	1.75	9.55	63.4
Esure	2	69.1	99.0	1.99	1.79	57.5
A&A Group	3	98.6	9.0	1.55	0	-
Fresh	3	96.6	0.0	1.75	0	-
Acromas	3	100.0	24.8	2.24	14.53	68.6
Admiral	4	98.4	48.5	3.34	5.78	99.1
RBS	4	100.0	46.6	3.46	17.56	92.7
Hastings	4	100.0	99.3	3.99	0.64	100.0
MMA Group	5	90.9	49.0	4.41	2.51	100.0
BDML	6	100.0	16.8	4.39	0.06	50.0
Ageas	6	100.0	50.9	5.45	0.03	66.7
BGL Group	12	100.0	96.1	11.93	2.59	75.3
Multi-Brand Firms	62	93.9	49.3	52.5	61.08	82.2
Single-Brand Firms	21	69.9	100.0	21.0	21.14	-
All Firms	83	80.2	78.1	73.5	82.22	-

Note: * Price sets in which firm quotes. Brand advertising expenditure is for 2010, sourced from the Nielsen Company.

Table 2: Mean Price and Price Dispersion by Car Type

Car type:	Fiesta	Focus	Vectra	BMW	MX-5
Mean Price:					
All Brands	£626	£713	£977	£1,217	£929
Single Brand Firms	£647	£738	£1,044	£1,192	£963
Multi-Brand Firms: All brands	£620	£705	£959	£1,224	£920
Multi-Brand Firms: Lowest brand	£577	£671	£912	£1,080	£852
Coefficient of Variation:					
All Brands	0.436	0.444	0.415	0.375	0.436
Single Brand Firms	0.382	0.417	0.467	0.395	0.471
Multi-Brand Firms: All brands	0.430	0.434	0.379	0.356	0.396
Multi-Brand Firms: Lowest brand	0.255	0.307	0.300	0.286	0.303

Notes: Calculated for indicated brands across the 88 price sets for each car type.

Table 3: Price Rankings of Multi-Brand Firms

Firm	Number of Brands	Mean Variance of Price Ranking	Mean Price Ranking	Mean Correlation Coefficient
Europa	2	0.214	0.397	-0.12
Zurich	2	0.001***	0.451	0.99
Brightside	2	0.060	0.443	-0.41
RSA	2	0.008***	0.866	0.36
AXA	2	0.008***	0.504	0.80
Esure	2	0.001***	0.025	0.77
A&A Group	3	0.043	0.651	0.36
Fresh	3	0.156	0.678	0.22
Acromas	3	0.050	0.256	-0.41
Admiral	4	0.001***	0.548	0.99
RBS	4	0.029**	0.573	0.36
Hastings	4	0.027*	0.277	0.79
MMA Group	5	0.052	0.620	0.46
BDML	6	0.034**	0.681	0.41
Ageas	6	0.087	0.511	0.06
BGL Group	12	0.023***	0.446	0.61
All	83	0.085	0.5	-0.01

Note: Variance is calculated across brands of each firm for each price set and the mean figure is reported. The comparison is based on paired observations under a t-test, *** = significant at 1%, ** = 5% and * = 10% level. Correlation correlations calculated for each pair of brands for each firm across all price sets in which both prices are posted, and the mean figure is reported.

Table 4: Summary Statistics for Brand Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
MULTIBRAND	0.78	0.41	0	1
ADVERT	5.81	6.38	0	16.61
*ADVERT*MULTIBRAND*	4.44	6.11	0	16.61
AFFINITY	0.34	0.47	0	1
POST	0.11	0.13	0	0.48
MMA GROUP	0.06	024	0	1

Sources: Authors' dataset, except *ADVERT* (£'m, 2010), which is sourced from the Nielsen Company.

Table 5: Results for Brand Price Ranking

Dependent variable: *RANK*	Maximum Likelihood				Logistic
	(1)	(2)	(3)	(4)	(5)
MULTIBRAND (β_1)	-0.249***	-0.159***	-0.128***	-0.097***	-1.531***
STRATEGY (β_2):					
ADVERT	-0.024***	-0.007***	-	-0.018***	-0.139***
*ADVERT*MULTIBRAND*	0.021***	-	-	0.016***	0.120***
AFFINITY	0.151***	0.154***	0.125***	-	0.882***
POST	0.626***	0.570***	0.537***	-	3.889***
MMA GROUP	0.221***	0.201***	0.193***	-	1.186***
Constant (β_0)	0.868***	0.815***	0.716***	0.952***	2.433***
MULTIBRAND (λ_1)	-0.120***	-0.088***	-0.099***	-0.074***	-0.935***
STRATEGY (λ_2):					
ADVERT	-0.008***	0.002***	-	-0.004***	-0.059***
*ADVERT*MULTIBRAND*	0.013***	-	-	0.008***	0.084***
AFFINITY	-0.042***	-0.043***	-0.046***	-	-0.460***
POST	0.210***	0.179***	0.157***	-	1.259***
MMA GROUP	-0.005	-0.006	-0.006	-	-0.119***
Constant (λ_0)	0.249***	0.258***	0.267***	0.207***	1.849***
Log Likelihood	-1,031.66	-1,620.79	-1,818.80	-2,437.24	-51,052.2
χ^2 [AIC]	8,192.43	5,683.29	5,284.22	5,840.78	6,911.11
Observations	28,327	28,327	28,327	28,327	28,327

Notes: Estimation of equation (2). In each case, controls included for the brand market share, consumer satisfaction, broker, product and price set dummies for individual and car type and date. *** = significant at 1%, ** = 5% and * =10% level.

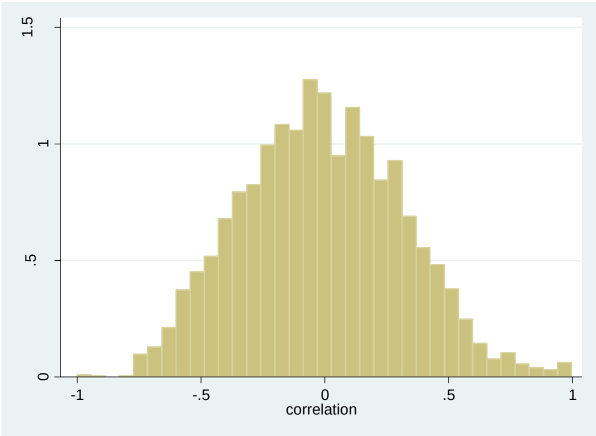
Table 6: Estimated Firm Coefficients for Price Rankings

Firm / Number of Brands		β_1	λ_1	β_1	λ_1
Two Brands		-0.391***	-0.035***	-	-
Three Brands		-0.537***	-0.058***	-	-
Four Brands		-0.348***	-0.128***	-	-
Five Brands		-0.093***	-0.073***	-	-
Six Brands		-0.203***	-0.093***	-	-
Twelve Brands		-0.169***	-0.157***	-	-
Europa	2	-	-	-0.201***	-0.020*
Zurich	2	-	-	-0.335***	-0.037***
Brightside	2	-	-	-0.163***	-0.127***
RSA	2	-	-	-0.035***	-0.265***
AXA	2	-	-	-0.292***	-0.191***
Esure	2	-	-	-0.711***	-0.348***
A&A Group	3	-	-	-0.049***	-0.101***
Fresh	3	-	-	0.065***	-0.024***
Acromas	3	-	-	-0.460***	-0.175***
Admiral	4	-	-	-0.456***	-0.115***
RBS	4	-	-	-0.985***	-0.187***
Hastings	4	-	-	-0.360***	-0.107***
MMA Group	5	-	-	0.033***	-0.079***
BDML	6	-	-	0.059***	-0.160***
Ageas	6	-	-	-0.321***	-0.046***
BGL Group	12	-	-	-0.203***	-0.153***
Log Likelihood		-457.6		2,605.7	
χ^2		9,178.4		103,926.4	
Observations		28,327		28,327	

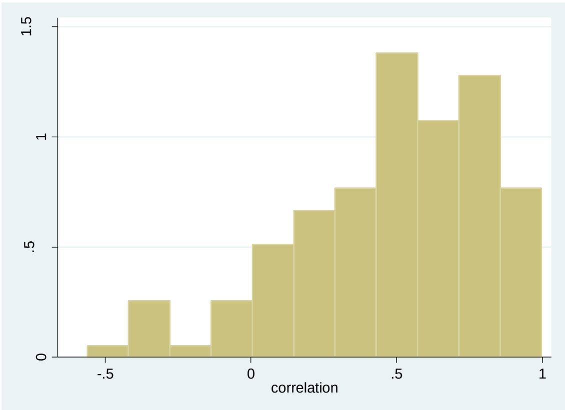
Note: Estimation of equation (2) with *MULTIBRAND* in spline form for number of brands owned by firms and for multi-brand firms. *** = significant at 1%, ** = 5% and * = 10% level.

Figure 1: Distribution of Correlation Coefficients for Brand Rankings

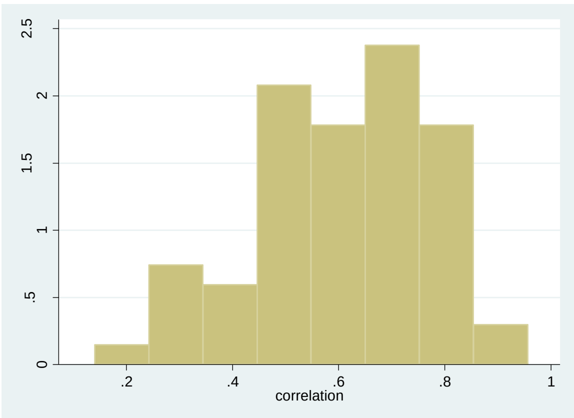
a: All Firms



b: Multi-Brand Firms



c: Multi-Brand Firms excluding the BGL Group



Appendix Table 1: Mean Number of Brands Posted by Firms by Individual Characteristics

Firm	Number of Brands	Age (years)				Occupation				Sex	
		25	40	55	70	Unemployed	Factory Worker	Computer Consultant	Retired	Male	Female
Europa	2	1.20	1.24	1.24	1.25	1.23	1.22	1.24	1.25	1.23	1.22
Zurich	2	1.38	1.36	1.37	1.38	1.37	1.37	1.36	1.38	1.00	1.74
Brightside	2	1.58	1.69	1.69	1.75	1.70	1.63	1.63	1.74	1.68	1.66
RSA	2	1.58	1.73	1.75	1.75	1.66	1.71	1.71	1.75	1.69	1.73
AXA	2	1.98	2.00	1.67	1.00	-	2.00	1.99	1.00	1.75	1.75
Esure	2	1.98	1.99	1.99	2.00	-	1.98	1.99	2.00	1.99	1.99
A&A Group	3	1.74	1.73	1.38	1.00	1.17	1.90	1.91	1.00	1.54	1.55
Fresh	3	1.75	1.75	1.76	1.75	1.75	1.75	1.76	1.75	1.75	1.76
Acromas	3	1.99	2.00	2.62	2.23	2.08	2.33	2.33	2.24	2.24	2.25
Admiral	4	3.38	3.37	3.43	3.39	3.39	3.38	3.40	3.44	2.84	3.98
RBS	4	2.98	3.49	3.72	3.73	3.38	3.40	3.41	3.74	3.45	3.47
Hastings	4	3.98	3.99	3.99	4.00	3.95	4.00	4.00	4.00	3.97	4.00
MMA Group	5	4.25	4.48	4.47	4.45	4.36	4.43	4.41	4.45	3.82	4.89
BDML	6	4.20	4.34	4.49	4.75	3.63	4.64	4.68	4.74	4.35	4.44
Ageas	6	5.38	5.53	5.55	5.00	4.78	5.76	5.81	5.43	5.39	5.50
BGL Group	12	11.97	11.91	11.94	11.95	11.97	11.97	11.88	11.94	11.95	11.93
Total	62	48.38	50.36	51.39	50.83	45.54	52.07	52.35	51.36	48.38	52.09

Note: Mean number of brands posted by firm across price sets in which it quotes (see table 1). A maximum of 62 brands may be quoted for each individual type.

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