Price Dispersion and the Ability to Search: The UK Internet Motor Insurance Market

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Abstract

The paper examines the link between price dispersion and search ability in the UK Internet motor insurance market. The negative relationship between price dispersion and search is shown in the presence of insurance risk. The paper uses price data from motor insurance websites for five car types and twenty-two individual types by age, occupation and sex, where the latter serve as proxies for search ability. It finds that price dispersion varies by individual type. The results are incompatible with alternative explanations, and support the role of search ability, implying that price dispersion will persist in online markets.

Key words: Price dispersion, search ability, Internet, insurance markets.

JEL Classification codes: L11, D83, D40.

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1. Introduction

Search costs are lower in online markets, but while it has been shown that the dispersion of prices falls as more people gain access to these markets (Brown and Goolsbee, 2002), price dispersion remains pervasive online (e.g., Smith and Brynolfsson, 2001; Baye *et al.,* 2004; Haynes and Thompson, 2008). It is well known that the observed price dispersion can arise from heterogeneous consumer search costs (Carlson and Pescatrice, 1980; Dahlby and West, 1986; Sorensen, 2000), but in the case of Internet markets the source of this heterogeneity is uncertain. It could be that individuals differ in their search propensity due to differences in income, prices or the opportunity cost of time, or it could be that they differ in their online search ability (Hargittai and Shafer, 2006). The distinction between these is important, as they have different implications for the nature of price dispersion and for policy.

The purpose of this paper is to examine the relationship between consumer search behaviour and price dispersion in Internet markets, focusing on the role of ability to search. The difference in search ability between individuals is of interest, since this may provide an explanation for the persistence of price dispersion in online markets.[1] The paper uses price quote data from an Internet motor insurance market, which enables prices to be matched directly to individual characteristics. Since individuals vary in their frequency of Internet use (i.e. time spent searching for prices and other online activities), these serve as proxies for search behaviour and in particular for online search ability. This follows by a 'learning-

[1] As far as we are aware this is the first paper to explore this issue. In general, studies focus on online price dispersion in terms of differences in behaviour across countries (Gatti and Kattuman, 2003; and Bock *et al.*, 2007), product characteristics (Chen and Scholten, 2003) or the firm type (Pan *et al.*, 2002), rather than search. Bayliss and Perloff (2002) attribute online price dispersion to search behaviour in general by ruling out non-search explanations.

by-doing' argument (Arrow, 1962), whereby more frequent users acquire better Internet skills and are better able to search. In particular, more Internet-savvy individuals are likely to find more prices, perhaps due to the greater use of comparison websites.

The use of insurance market data offers clear advantages, but the expected claim or insurance risk varies according to the individual characteristics and will also be reflected in the price. This is problematic as risk makes lower-priced insurance contracts relatively less attractive to the firm, affecting the level of price dispersion. It arises because homogeneous contracts to a given type carry an identical risk, but as risk increases the firm must sell more lower-priced contracts to get the same expected return as from the higher-priced contracts. From a theoretical standpoint, the relationship between price dispersion and search costs is well established (Salop and Stiglitz, 1977; Varian, 1980), but a contribution of this paper is to demonstrate this relationship in the presence of risk. It is shown that search lowers price dispersion in insurance markets, but only when the search is sufficiently high. Further, this occurs at a higher level of search compared to non-insurance markets.

The data used in this study are gathered from the most popular UK motor insurance comparison site and from the websites of leading motor insurance brands that do not quote on comparison sites. By taking-on assumed identities, price data are collected for twenty-two individual types according to age, occupation and sex. This is for five car types and for twelve months, giving 1,320 price sets, consisting of about 32,000 individual quotes. The empirical results show that price dispersion varies significantly across these individual characteristics, such that in general price dispersion in the motor insurance market is lower for the young and employed. The results are consistent with the frequency of Internet use, but incompatible with alternative explanations such as propensity to search, Internet access and within-group heterogeneity, so that it is argued that they reflect search ability.

In the next section, the relationship between price dispersion and search is modelled in the presence of risk. Section 3 sets out the data and section 4 contains the main empirical work. The results are discussed in section 5 and conclusions are drawn in section 6.

2. Price Dispersion and Search in Insurance Markets

The aim of this section is to analyse the relationship between price dispersion and search in which insurance risk is present. The model is general to any insurance market, although it captures some special features of the motor insurance market, which is made-up of sub-markets (j, k) related to the individual j (= 1, 2, …, J) and car types k (= 1, 2, …, K).[2] The approach is to consider the price distribution for a representative sub-market (j, k), and then to examine the effect of the search parameter on price dispersion. In so doing, it is assumed that the market as a whole clears, so that the variables are at their equilibrium values.[3] To support this, each firm posts at most a single price in a sub-market and there is free entry and exit to the industry as a whole. Two conditions must hold in equilibrium. First, any price in a sub-market must yield the same expected return to the firm, so that posting a low price must give the same expected return as posting a high price. Second, each firm in the industry receives the same industry level of (zero) expected profits.

These assumptions are reasonable for the market under consideration, as firms can freely vary their price within a sub-market, while the motor insurance market is competitive, so that firms generally do not make underwriting profits. On average 25 firms are observed to quote in each of our sub-markets, while the low profitability of this industry is reported

[2] For some insurance markets, such as home insurance, the model is entirely appropriate, as both house and individual characteristics are relevant, the latter for search. For other markets, such as health, price quotes may depend on individual characteristics only, which involves holding k constant.

[3] As such, the interest is in the sub-market rather than the market as a whole, so that we set out the conditions that allow the sub-market price distribution to be derived consistent with equilibrium in the market as a whole. There is no advantage to solving the model explicitly, as this complicates the analysis, but leading to the same expression for distribution of sub-market prices in (3) below. The model is necessarily simplified in order to draw out the main features, so that, for example, firms do not post multiple prices or play mixed strategies, either in sub-market entry or in price. There are also a sufficient number of firms to cover each sub-market.

by Data Monitor (2008). The firms are risk neutral, and the expected return in sub-market (j, k) is denoted R_{jk} (> 0), where each firm posting a price sells that number of contracts to earn this return.[4] For generality, returns vary across sub-markets, as while incumbents offer insurance repeatedly and know about consumer search in their sub-markets, it is reasonable that potential sub-market entrants do not have knowledge of each segment. For this reason, not all firms enter every sub-market, but in equilibrium each firm makes the same industry level of expected profits across the sub-markets in which they quote.[5]

2.1 Search Behaviour

Motor insurance quotes are consumer specific, so firms cannot engage in price advertising and prices can only be discovered through search. Search is modelled as a fixed sample, non-sequential process, in which consumers discover multiple prices simultaneously. Non-sequential search is considered elsewhere (Wilde and Schwatz, 1979; Janssen and Moraga-Gonzàlez, 2004), although it is less common than either sequential search (Rob, 1985; Stahl, 1989) or the clearinghouse model (Baye *et al.*, 2001; Morgan *et al.*, 2006). It does not exactly fit this market but it is the closest approximation. This is because a single search on a comparison website yields multiple prices, so that it cannot be sequential search. Further, the leading UK motor insurance brands do not to quote on comparison sites, so that a single search does not reveal all prices and the clearinghouse model is also unsuitable.[6]

Formally, focusing on a single sub-market and dropping the (j, k) subscripts for now, suppose that there exists a finite set of n (≥ 2) posted prices $p = (p_1, p_2, \ldots, p_n)$, where $0 < p_1$

[4] Motor insurance is a legal requirement, and since there are assumed to be no uninsured drivers, then the risk preferences of individuals are not considered. Given R_{jk} firms are unable to cross-subsidise their activities.
[5] The sub-market returns are set against the costs for each firm, which are fixed in nature, comprising such things as the setting-up of a website, software development, actuarial costing, premises and so on.
[6] At the time of data collection, four leading brands did not quote on the most popular UK motor insurance price comparison site, *confused.com*, together accounting for a market share of about 30%. It is still the case that heavily advertised brands choose not to quote on online price aggregators.

$< p_2 < \ldots < p_n$. Let N denote the number of homogeneous individuals in the sub-market, where each of these undertakes the same fixed sample search of size m ($1 \leq m \leq n$), which is the exogenous search intensity. The individuals select the lowest searched price, but since they sample prices randomly (at a sample size of m) then this leads to a density function for distribution of selected prices, which is represented by the exponential function:

$$f(p{:}m, p_1) \quad = \quad m \, \exp[m\,(p_1 - p)], \tag{1}$$

where for convenience p is continuously defined and $\int_{p=p_1}^{p=\infty} f(p{:}\, m,\, p_1) = 1$.[7] This has the desirable properties, since the variance and mean of f are:

$$\operatorname{var} f(p : m, p_1) = \frac{1}{m^2} \quad \text{and} \quad \operatorname{mean} f(p : m, p_1) = p_1 + \frac{1}{m}. \tag{2}$$

Thus, as the level of search intensity m increases the variance tends to zero while the mean price falls towards p_1, such that in the limit the lowest price p_1 is always selected. The probability density functions for the selected price is sketched in Figure 1 for the illustrative case $n = 7$ with $m = 1, 2, \ldots, 7$. It demonstrates the above properties.

2.2 The Distribution of Sub-Market Prices

To describe the distribution of sub-market prices it is supposed that firms post their prices in the knowledge of consumer search, so that only selected prices are posted, and the sets of posted and selected prices are therefore identical. In practice, firms quoting in a sub-market have experience of pricing repeatedly over time, so they are able to observe demand, and in

[7] The usual expression for the exponential function is obtained by setting $p_1 = 0$, in (1), in which case the mean and variance in (2) are $1 / m$ and $1 / m^2$, where $1 / m$ is the scale parameter. The proof for this result and those in (2) below are given in McDonald (2010).

this way they gain knowledge of consumer search. In each sub-market (j, k) the insurance contracts are homogeneous in the car type, coverage and risk, so that each contract has the same expected claim, denoted C_{jk}. This means that the expected revenue that can be earned on a contract at each price p_{rjk} is p_{rjk} - $C_{jk} \geq 0$. The risk affects the price distribution, as in equilibrium a firm must sell relatively more lower-priced contracts to make R_{jk}.

Given this, dropping (j, k) subscripts, the distribution of sub-market prices is:[8]

$$h(p\colon m, C, p_1) = \frac{(p-C)\ m\ \exp[m\{p_1 - (p-C)\}]\ N}{R}. \tag{3}$$

At each price $p_r \in p$ the numerator gives the expected revenue that can be earned across all firms in the sub-market at that price, while the denominator is the equilibrium return earned by a single firm, so that the ratio of these gives the number of firms offering p_r. Hence, as p_r varies then (3) gives the distribution of observed sub-market prices. The first term in the numerator of (3) is the expected revenue on a contract at a price p_r, the second term is the probability that p_r is selected as the lowest price by (1) and N is the sub-market size.

Price dispersion is examined using the variance, where from the moment-generating function of (3) it is shown in the Appendix that:[9]

$$\operatorname{var} h(p : m, C, 0) \quad = \quad \operatorname{mean} h(p : m, C, 0)\ [\lambda \text{ - } \operatorname{mean} h(p : m, C, 0)], \tag{4}$$

$$\text{where} \quad \operatorname{mean}\ h(p : m, C, 0) \quad = \quad \exp(mC)\ \frac{(2 - mC)}{m^2}\ \frac{N}{R}, \tag{5}$$

$$\text{and} \qquad \lambda \quad \equiv \quad \frac{6 - 2\,m\,C}{m\,(2 - m\,C)}. \tag{6}$$

[8] To make the search comparable across sub-markets, C is deducted from p in the exponential term. Since $p \geq C$ then (3) is non-negative for any price p_r. Since each firm offers at most one price in a sub-market, then to consider the price distribution it is sufficient to consider the number of firms offering each price.
[9] For tractability, it is necessary to set the minimum price p_1 equal to zero when considering the variance of h.

To ensure that the mean price in (5) is positive, it is necessary to suppose that search is not too high relative to the risk, i.e. $0 < C < 1 / m$. This accords with intuition as it means that the mean price is positively related to risk C and negatively related to search m. To examine the effect of search on the variance, differentiation of (4) gives:

$$\frac{\partial \operatorname{var} h(p : m, C, 0)}{\partial m} = \frac{\partial \operatorname{mean} h(p)}{\partial m} \left[\lambda - 2 \operatorname{mean} h(p)\right] + \operatorname{mean} h(p) \frac{\partial \lambda}{\partial m}.$$

Since both the mean price in (5) and λ in (6) are negatively related to m, then the sign on this derivative depends on the term in square brackets, which is signed according to:[10]

$$\frac{\lambda}{2} > \operatorname{mean} h(p : m, C, 0) \quad \text{if} \quad m > \left[\frac{2 \exp\left(2 - \sqrt{2}\right)}{1 + \sqrt{2}}\right] \frac{N}{R}. \tag{7}$$

Hence, the variance of the price dispersion is negatively related to search provided that the level of search is sufficiently high, such that (7) is satisfied. If (7) does not hold then price dispersion may increase with search. As intuition, when $m = 1$, each consumer samples a single price and each firm offers the same (monopoly) price as no firm has an incentive to offer less than this, so that the variance is zero. However, as consumers search more, it is advantageous for some firms to lower prices to capture these consumers and the variance increases, but as search increases further then the variance must eventually fall.

A similar result to this is obtained elsewhere (e.g. Stahl, 1989; Janssen and Moraga-Gonzàlez, 2004), but in this case the result is derived in the presence of risk. It is possible to compare this result to the no-risk case by setting $C = 0$, in which case:[11]

[10] This sufficient condition is derived in the Appendix. It can be shown that λ is negatively related to m when $m\,C < 3 - \sqrt{3}$, which is satisfied since $0 < C < 1 / m$ by the above.
[11] This condition, which is now both necessary and sufficient, is derived in McDonald (2010).

$$\frac{\partial \operatorname{var} h(p : m, 0, 0)}{\partial m} < [>] \, 0 \quad \text{iff} \quad m > [<] \, \frac{8}{9}\frac{N}{R}. \qquad (8)$$

The term in square brackets in (7) is approximately equal to 3 / 2, so that comparison with (8) suggests that in the presence of insurance risk there is a smaller range for *m* over which the variance of prices is negatively related to search. This arises because risk makes lower-priced contracts relatively less attractive to firms, so that greater levels of consumer search are required in order to induce firms to offer lower prices in insurance markets.

Finally, since λ is increasing in C in (6), it can be shown that (7) is sufficient for the variance to increase with risk, i.e. $\partial \operatorname{var} h / \partial C > 0$. However, since the mean price in (5) increases in C then the variance increases at a decreasing rate with the insurance risk. The relationship between price dispersion and search is now examined empirically for the motor insurance market. This is based on a regression analysis across sub-markets.

3. The Data

The data were collected at monthly intervals over a one-year period from February 2006 to January 2007, both from the main UK motor insurance comparison website, *confused.com*, and directly from the websites of the four leading motor insurers not listed on comparison sites.[12] At 2007, *confused.com* had a two-thirds market share of motor insurance policies sold in the UK via an online aggregator (*Financial Times*, 2007) and claimed to cover 94% of firms. For our purpose, a firm is a distinct maker of quotes, with the three main methods of selling motor insurance represented on this site.[13] By taking on assumed identities, price

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[12] These are Churchill, Direct Line, Esure and Tesco. These insurers are heavily advertised with large market shares and it is reasonable that consumers wishing to sample prices will consider these sites.

[13] An underwriter may sell insurance direct to the consumer, through an exclusive relationship with a firm or firms (e.g. a branded product or products), or through a broker that deals with a range of underwriters.

quotes were gathered in respect of individuals who were allowed to vary according to three personal characteristics: by age, by sex and by occupation.

Table 1 shows that the frequency of Internet usage declines with age and is greater for males than for females. The table refers to Internet users only, and it indicates a clear difference in usage by age, although less pronounced by sex. It is expected that more frequent users will acquire better Internet skills and be better able to search, so that age and sex are used as proxies for the ability to search. In addition, search ability is likely to vary by occupation, since higher-skilled jobs will involve higher levels of education and greater computer use. Similar arguments are made by Savage and Waldman (2009), who measure the technical ability of Internet users by education and by the number of years online.

In collecting the data, four ages are selected, 25, 40, 55 and 70 years, which cover a good age spread, with fewer firms quoting outside this range. Data are also collected by males and females, and for the blue- and white-collar occupations of a 'factory worker' and 'computer consultant', where the latter is expected to be more skilled at search.[14] To these are added an 'unemployed individual', who on average is likely to be less skilled, and a 'retired person', which embodies heterogeneous characteristics that includes the so-called 'silver-surfers' as well as the inactive. For realism, 70-year olds are retirees only, while 25- and 40-year olds are not retired, so that in total there are 22 individual consumer types.

3.1 Other Policy Characteristics

The UK Society of Motor Manufacturers and Traders defines nine car market segments, and car types were chosen as the leading model in five of these, based on total UK sales at the year 2000. These are the Ford Fiesta Encore (13.3% of sales in the Super-mini car

[14] The direct insurers do not permit search at this level, so that 'manual' or 'manufacturing and engineering' and 'professional' or 'scientific and technical' are instead specified.

segment in the year 2000), the Ford Focus Zetec (17.3% of the Lower Medium segment), the Vauxhall Vectra CD 16V (14.3% of Upper Medium cars), the BMW 525i (12.9% of Executive cars) and the MG MGF (8.6% of Sports cars).[15] Each model is six years old, which is the median UK car age (SMMT, 2006). Details of the car types are given in table 2, which shows the car values, total sales and a risk index. According to this, the BMW is the highest risk car, while the Fiesta and Focus are relatively low-risk models.

Motor insurance quotes can vary substantially by location, even from street to street, so that a single address was selected. This is for a reasonably affluent suburb of Newcastle-upon-Tyne, which has a mean house price close to the national pattern by four house types, i.e. flats, terraces, semi-detached and detached.[16] As many as possible of the other motor insurance policy details were held constant, and chosen to reflect average market conditions, including a fully comprehensive level of cover, an annual mileage of 9,000 miles, and business, commuting and social use. All drivers have a 5-years no-claim bonus.[17] The data were collected for the lowest quoted premium and for the associated compulsory excess. Consumers may vary the voluntary excess amount, but this was set to zero.

3.2 Data Description

The data relate to a total of 110 sub-markets, i.e. 22 individual and 5 car types, and since they were collected for a twelve-month period there are 1,320 price sets. These form the

[15] Other segments are the Mini and Luxury vehicles, which are small markets, and the Multi-Purpose and Dual Purpose vehicles (e.g. Sports Utility Vehicles), which are similar to the Upper Medium segment.
[16] This is for a street in the Gosforth postcode district. To select this, 40 streets were randomly sampled, and a street was chosen with a standard deviation of quoted prices across firms closest to the mean deviation. 25 firms offered prices for some or all of the 40 streets, of which 13 offered the same price at each location. Of the remainder, the greatest standard deviation across locations for any firm was 14.7% of the mean premium.
[17] Other features were set to zero, including the no-claims bonus protection and legal fees cover. Few firms include the latter as standard, although many include a courtesy car, which was therefore requested. Policies may vary in other details that cannot be controlled by the consumer, such as windscreen or audio equipment cover, but these are generally minor and confined to the small print, so that for practical purposes the policies are assumed to be homogeneous in these respects.

basis for the regression analysis below. In total, there are 32,255 observations on prices from 41 firms, but entry and exit mean that the number of firms quoting in each month is between 31 and 36 firms, of which 27 quote in every month. Each firm is associated with no more than one price in a price set, with the mean number of prices in a price set equal to about 24, but varying between a minimum and maximum of 11 and 31 prices. For the MGF the mean number of prices is 19.7, but between 23.6 and 26.0 for the other car types.

Descriptive statistics for the 1,320 price sets are given in table 3, disaggregated by the individual and car type. The mean premium increases with the risk index of the car (see table 2), but within this there is a consistent pattern across the individual types, with higher premiums generally paid by those that have higher accident rates or more severe accidents, e.g. 25 year-old males. The coefficient of variation is shown in the parentheses in table 3, and in general there is much less variation for this than for the mean.

4. Empirical Results

The estimation equation is specified to capture the terms, *m*, *N*, *R* and *C*, in the model:

$$\begin{aligned} CV_{jkt} \;=\; & \alpha + \beta_1\, AGE_{jk} + \beta_2\, OCC_{jk} + \beta_3\, SEX_{jk} + \gamma_1\, MARKET_k - \gamma_2\, RETURN_{jk} + \gamma_3\, COMP_{jk} \\ & + \gamma_4\, RISK_{jk} - \gamma_5\, RISK^2_{jk} - \gamma_6\, EXCESS_{jk} + \gamma_7\, OPT_{jk} + \text{dummies}_{jkt} + \varepsilon_{jkt}. \end{aligned} \tag{9}$$

This is regressed across price sets, i.e. for each of 110 sub-markets (j = 22 individual types and k = 5 car types) for each of t = 12 months.[18] The dependent variable measures the price dispersion using the coefficient of variation of prices (*CV*) for each price set, where prices

[18] This gives 1,320 price sets, but owing to some errors in data collection seven cases are dropped.

are measured in natural log form. Other variables are described below, where ε is a random error term. Each γ_i is positive, so that (9) signs the expected effect of these terms.

4.1 The Variables

The search terms *m* are measured by binary variables for the age (*AGE*), occupation (*OCC*) and sex (*SEX*) of the individual. According to the above discussion, these terms are proxies for online search ability, and our expectation is that price dispersion should increase with age, be lower for the skilled employed, and if anything be greater for females. Of course, it is possible that these terms may pick up other search-related explanations, such as Internet access or the propensity to search due to differences in income, prices or time. This issue is considered in section 5, although if the variables capture the propensity to search then the sign on some of these is likely to be reversed. For example, the unemployed are expected to have the lowest search ability and greater price dispersion, but their lower income could lead to a greater search propensity in which case this should lead to lower price dispersion. Likewise, a retired individual may have a lower ability to search, but be more time rich.

As regards the other variables, the size of each car market (*MARKET*) in table 2 is used as a proxy for the size of the sub-market *N*. Ideally, this would be measured at the sub-market level, but these data are not available. To measure the sub-market return *R* the number of firms in each price set (*RETURN*) is used. This is a useful measure since if the returns are greater in some sub-markets then more firms will be induced to quote. This may seem counter-intuitive, as more firms imply greater competitive pressure leading to lower returns, but to capture this market-wide effect we include the total number of firms quoting in the market as a whole in each month (*COMP*). Like elsewhere, *COMP* has an expected positive effect on price dispersion (Haynes and Thompson, 2009).

Since riskier sub-markets are characterised by a higher mean premium (see table 3), the level of risk C is measured by the mean premium of the price set (*RISK*). As the cars vary in value, then to make the estimated coefficients comparable across car types, *RISK* is centred about the mean premium across all price sets for each car type. The model predicts that price dispersion increases with risk but at a decreasing rate, so that this term is included as a quadratic. The voluntary excess was set to zero, but a compulsory excess was required for about 90 per cent of quotes, being almost always requested for the BMW and MGF cars. This lowers the firm risk, potentially affecting the price dispersion, so it is also included in log form as an explanatory variable (*EXCESS*), and it has an expected negative sign.[19]

Finally, firms differ in their efficiency and market strategy, so that *OPT* terms are included for the number of firms that declare themselves as opting-out of individual (*OPTI*) or car (*OPTC*) sub-markets, which are interpreted below. It could be that price dispersion reflects unobserved hetereogeneity in consumer tastes for quality differences across firms. For example, some firms may have a reputation for easier claim settlements. To the extent that this is an issue then a binary term is included for each firm that takes a value of unity if the firm quotes in a given price set. It may also be the case that consumer types differ in other characteristics, such as the level of brand loyalty or the use of other search channels, and these issues are discussed below. Time monthly dummies are included throughout.

4.2 Estimation Results

The results from regressing (9) for the five car types are reported in table 4. The first three

[19] Regressing the excess on the premium and dummies for the car type gives a significant negative coefficient of 0.06, indicating that each £1 increase in the premium reduces the excess by 6p. To allow for the excess, certainty equivalent premiums were calculated for each premium-excess quote that were based on a range of assumptions about the risk preferences of consumers, but making no qualitative difference to the results, so that the price data are not adjusted for the excess. The results for these can be found in McDonald (2010).

columns pool the data across the cars using different measures of price dispersion, with the first column using the coefficient of variation (*CV*) as the dependent variable, and the other two columns using the standard deviation and the range.[20] These give qualitatively similar results in table 4, so that attention focuses on the *CV* measure, which is used for each car type in the remainder of the table. The results give a good fit to the data.

The interest is in the estimates for the individual types, *AGE*, *OCC* and *SEX*, which capture the effect of search on price dispersion. In each regression the base case is a 25-year old, unemployed male. A cursory inspection of the coefficients on the search terms in table 4 suggests that the signs and magnitudes of these can vary substantially across the car types, raising an issue about whether the data can be pooled. In fact, whether considered individually or together the estimates on the search terms differ significantly across the cars in the pooled regression.[21] It suggests that there is interaction between the individual and car types, influencing the effect of search on price dispersion, and it is considered further below. It means that the results in the first three column of table 4 give an average effect across car types, and which therefore cannot be taken as representative of any particular car. Before discussing the search terms, the estimates on the non-search variables in table 4 are briefly considered. These are generally significant and signed as expected.

A few exceptions to this are the estimates on *MARKET* and *COMP,* although neither is wholly surprising. The first of these is not available at the sub-market level, while for the latter there is little monthly variation in the total number of firms quoting in the market as a whole. As expected, the *RETURN* estimate suggests that sub-markets with higher returns

[20] The equation was also estimated using the 'gap' measure of price dispersion, which is the difference between the two lowest prices in a price set (Baye *et al*, 2004), but these results were unsatisfactory and not presented. Underlying the 'gap' measure is Bertrand, in which some consumers have full information and purchase at the lowest price, but this sits uneasily with the motor insurance market in which not all firms quote on a comparison site. These results support the use of the non-sequential search model.

[21] The null hypothesis that the search terms are the same across car types when considered individually was rejected at the 1% significance level in each case (at the 5% level for computer consultants). Likewise, when taken as a group the estimates on the respective search terms were always significantly different at the 1% level (the F-statistics relative to the Fiesta are: Focus, 9.03; Vectra, 27.74; BMW, 33.82; and MGF, 241.08).

have lower price dispersion, while both the opt-out terms are plausible. These suggest that firms dropping-out of markets by car type do so towards the middle of the price distribution (*OPTC*), which indicates more specialised markets, while those that drop-out from quoting for specific individuals (*OPTI*) do so at the extremes of the price distribution.

The estimates on the *RISK* terms offer support for the model, as not only does price dispersion increase at a decreasing rate with risk, but for a sufficiently high level of risk there is a negative relationship in the case of the MGF sports car. *RISK* is measured by the mean premium of the price set, which is the same as the denominator of the *CV* measure of price dispersion, but the results for the standard deviation in table 4 indicate that this is not an issue. Further, when the quadratic *RISK* term is omitted the other estimates are much the same, except that in the equation for all car types the *MARKET* term is significant. Finally, the coefficient on the *EXCESS* term is correctly signed where significant.

4.3 The Search Terms

The pooled results for *CV* in table 4 show that each of the search terms is significant, and that the pattern of estimates conforms to our earlier hypothesis that price dispersion should be lower with higher search ability. Price dispersion increases significantly with age at the 1% level, albeit there is no difference between the 55- and 70-year olds, while it is significantly lower for the employed compared both to the unemployed and the retired, although there is no difference between the two occupations. Females face lower price dispersion than males, but the magnitude of this difference is small, on which more is said below. The differences between the ages and the occupations are present even when the other individual characteristics are held constant, e.g. between 25- and 40-year olds, 40- and 55-year olds and all three of these for each of the unemployed, factory worker and computer consultant, and for males and females.[22] These results are consistent with the hypothesis, although there may be interaction between the individual and car types.

In the case of the car types, there is considerable variation in the sign and magnitude of the estimates on the search terms in the remainder of table 4, but this is from differences in the estimated coefficients for the base case, i.e. a 25-year old, unemployed male. In their *relative* magnitude the results for the search terms are consistent with those for the pooled regression, albeit with differences due to interactions between the individual and car types. The results for the five car types are now considered by age, occupation and sex.

In the case of age, the same pattern is evident for the Fiesta and Focus cars as for the pooled regression in table 4, while in the case of the other three car types the 40-year olds still have significantly lower price dispersion than the 55- and 70-year olds, each at the 1% level. The only difference is that a 25-year old driving these three cars no longer faces less price dispersion relative to the other ages, which gives the negative estimates on *AGE*. In table 2 it can be seen that the Vectra, BMW and MGF are higher-risk cars, and it is possible that the substantial risk associated with 25-year olds driving these cars is not controlled for, even though a 5-years no-claim bonus is stipulated.[23] This may be because fewer insurers quote for younger drivers of these cars, so that the distribution of prices is truncated and the mean premium does not adequately control for the risk. However, few young people drive these models and it may just be that relatively little search done on these prices.

The estimates on the occupation terms for the car types also support those for the pooled regression. In particular, the employed (i.e. factory worker and computer consultant) face significantly less price dispersion than the unemployed for four of the five cars, while

[22] All tests on these interaction terms were significant at the 1% level, except that there was no significant difference between the factory worker and computer consultant for each age and by sex.

[23] A similar result was obtained when the location of the policyholder was changed. This involved collecting data for the Ford Focus car for four contrasting locations. While qualitatively similar results were obtained overall, price dispersion was much greater for 25-year olds living in a deprived urban area (McDonald, 2010).

the employed have lower price dispersion than the retired for three cars (at the 5% level or higher). The prior expectation is that a computer consultant will have the greatest ability to search online, and this is consistent with the estimates for the Fiesta, BMW and MGF cars, while for the other cars there is no significant difference. The *OCC* estimates for the MGF are greater in magnitude, which reflects the unemployed facing greater price dispersion for this car (see table 3), for which the explanation is like that for the 25-year olds.

Finally, in the case of sex, there is no clear pattern in the estimates for the car types. In the pooled regression females actually face significantly less price dispersion, although the difference is small and dominated by age and occupation. The variation in Internet use is less pronounced by sex in table 1, and it may be that while women spend less time online, they spend more of this searching for prices, acquiring search-specific skills (Hargittai and Shafer, 2006), so that unlike age and occupation there are opposing factors. The difference in the sign between the Fiesta and Focus cars in table 4 may also be rationalised.[24]

5. Discussion of the Results

The empirical results indicate that there are significant differences in price dispersion for individuals with different personal characteristics. The contention is that these are due to differences in the ability to search, as lower levels of price dispersion are found for those individuals who are in general younger and the higher skilled employed. Of course, it was indicated above that there may be alternative explanations for these findings, so that before concluding it is important to consider these. They include the possibilities that the findings reflect risk rather than search or that they are due to some other search explanation.

[24] The Focus is a small family car, whereas the Fiesta is a small functional car, so that for females driving the latter cost considerations may be less important, which is a propensity to search story.

On the first of these, the model predicts that higher levels of risk will lead to greater price dispersion, but while some of the estimates reflect this, such as 25-year olds driving high-value cars, in general the results are not consistent with this explanation. Thus, more price dispersion is found for individuals that are known to be less risky (i.e. older drivers), while price dispersion exists for individuals where little or no variation in risk is expected (i.e. occupations). Risk could potentially explain the result for the unemployed, who face more price dispersion, but regressing the mean and minimum premiums across price sets on individual characteristics (of age, occupation and sex) indicates that it is not the case. The unemployed face higher mean premiums, but there is no significant difference in the results for the minimum premium, despite this being more likely to reflect risk.

This suggests that the regression estimates reflect search rather than risk, but rather than the ability to search it could be due to differences in the propensity to search that mean that some individuals spend more time searching for motor insurance. Both factors may be present and the results for the younger individuals are consistent with a propensity to search explanation, as these face higher prices and have lower incomes on average. However, the occupation results are incompatible with the search propensity, as relative to the employed, the unemployed and retired are likely to have lower incomes and a real cost of time, but the price dispersion is greater for these.[25] Likewise, when the retired individuals are interacted with age these results are also inconsistent with the propensity to search explanation. While the 55- and 70-year old retired have a similar opportunity cost of time, it may be expected that the 55-year olds have a lower propensity to search, as they can afford to retire early and presumably have a higher income. However, price dispersion is significantly lower for the 55-year old retirees, suggesting that it is the ability to search that matters.

Finally, it may be that the individuals differ in unobserved characteristics that affect

[25] If the propensity to search is also present this may potentially explain why the difference in price dispersion is more pronounced for age than for the occupations in table 4.

their online search. One possibility is that some individual types engage in lower levels of search as they have a higher proportion of loyal consumers, e.g. older consumers are likely to have more established relationships with particular insurers, but the posted prices reflect those individuals that actually search, so that there is no reason to suppose that this will affect online price dispersion.[26] Another possibility is that individuals differ in their level of online access or in their ability to search using other channels, such as by telephone or through a broker. However, if search by alternative channels matters, then online prices would have to be affected by offline behaviour, but it is well known that firms discriminate between Internet and non-Internet users (e.g. Brynjolfsson and Smith, 2000).[27] Hence, we do not believe that the results pick up unobserved heterogeneity in the characteristics.

6. Conclusions

This paper finds that price dispersion in the Internet motor insurance market varies with the individual characteristics of policyholders, such that it increases with age and is higher for the unemployed and retired compared to the employed. This is believed to reflect search behaviour, rather than risk, with the differences in the ability of individuals to search online the most plausible explanation for the differences in price dispersion. This is because the young and employed are likely to be more skilled in their online search activities, and so be able to find more prices for a given level of search. Given that the insurance companies are continually adjusting their prices in response to demand, then it is reasonable that the price distributions will reflect this. The results are incompatible with other explanations, such as in the search propensity due to differences in income, prices or the opportunity cost of time,

[26] In any case, in other work using the same data, but analysing the effect of advertising on pricing strategies, consumer loyalty is found not to increases with age (McDonald and Wren, 2011).

[27] Of course, Brown and Goolsbee (2002) find that the level of Internet access affects offline prices, but in their study of early Internet uptake the consumers that search online are constrained to purchase offline.

and so it appears to be the ability rather than the length of time searching that matters.

An implication of the paper is that even with the possibility of low-cost search using comparison websites and a high level of online access, price dispersion is likely to persist in Internet markets due to differences in search ability. It suggests that to make markets more competitive it is not sufficient to get individuals online, but that individuals need to have adequate Internet search skills. The results have been derived in the context of insurance markets, but they apply to any online market where there are different search abilities, and not just those markets where the product reveals information about the individual. The paper has established the standard result between price dispersion and search in insurance markets, and for future research this suggests that these insurance markets provide a useful way of linking price data with individual characteristics.

Table 1: Frequency of Internet Use

		Daily	Weekly	Less frequently
Age:	16-24 years	77	19	4
	25-44	72	20	8
	45-64	65	25	10
	65 plus	54	27	19
Sex:	Male	73	20	7
	Female	65	24	11

Source: Office of National Statistics, 2008.
Notes: Internet use within previous three months. Data not available by occupation.

Table 2: Car Types

Make and model	Engine size (cc)	Car value[a]	Total sales[b]	Risk rating[c]
Ford Fiesta Encore	1299	£1,595	91,783	4
Ford Focus Zetec	1596	£3,350	114,512	5
Vauxhall Vectra CD 16V	1998	£3,120	70,704	12
BMW 525i	2494	£8,065	13,443	16
MG MGF	1796	£4,320	5,766	12

Notes. a. *parkers.co.uk*, 6th February 2006. b. Sales at 2000, SMMT (2006). c. Advisory risk rating index of the Association of British Insurers based on the following: damage and parts costs, repair times, new car values, body shells, performance and security. The index lies between 1 and 20, where 1 is the lowest risk.

Table 3: Descriptive Statistics for the Premium

Car type:		Fiesta	Focus	Vectra	BMW	MGF
Age	25 years	373	389	570	905	692
		(0.12)	(0.12)	(0.14)	(0.22)	(0.25)
	40 years	269	281	403	526	465
		(0.13)	(0.13)	(0.12)	(0.11)	(0.22)
	55 years	212	223	306	400	371
		(0.18)	(0.16)	(0.16)	(0.13)	(0.28)
	70 years	223	232	325	414	384
		(0.21)	(0.18)	(0.18)	(0.16)	(0.26)
Occupation	Unemployed	299	316	455	653	577
		(0.14)	(0.13)	(0.14)	(0.16)	(0.42)
	Factory	281	293	417	600	486
		(0.14)	(0.14)	(0.15)	(0.16)	(0.17)
	Consultant	276	286	410	581	473
		(0.14)	(0.13)	(0.14)	(0.15)	(0.17)
	Retired	215	225	312	402	371
		(0.21)	(0.18)	(0.18)	(0.15)	(0.24)
Sex	Male	278	290	412	584	495
		(0.14)	(0.14)	(0.14)	(0.15)	(0.25)
	Female	267	280	400	562	448
		(0.17)	(0.14)	(0.15)	(0.16)	(0.25)
All individuals		273	285	406	573	486
		(0.15)	(0.14)	(0.15)	(0.15)	(0.25)

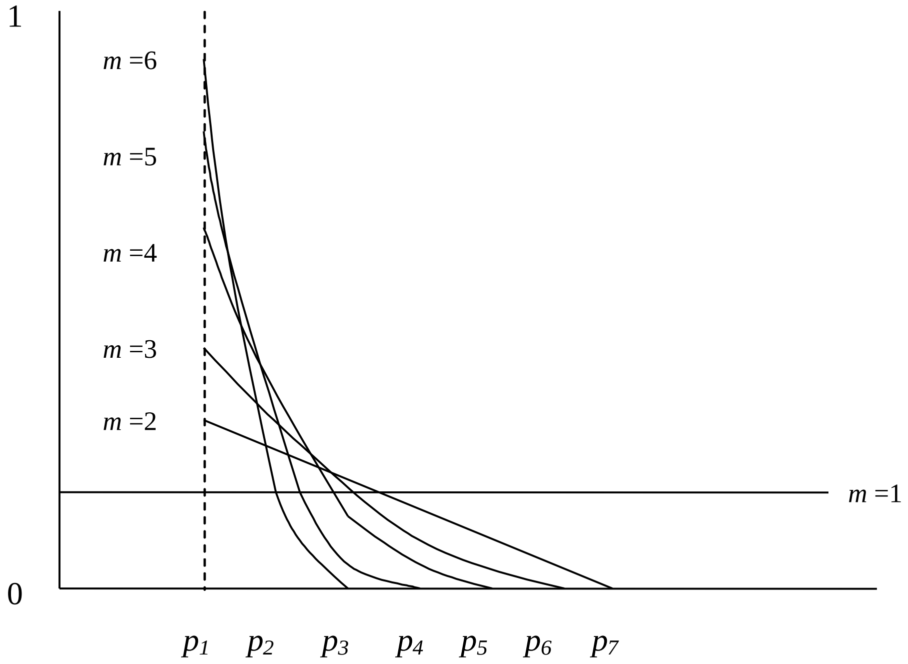
Notes. Mean premiums rounded to nearest £ and coefficient of variation (standard deviation divided by mean) in parentheses. Each is calculated as the mean across the relevant price sets. Excludes compulsory excess.

Table 4: Regression Results

Car type:	All cars (pooled regression)			Fiesta	Focus	Vectra	BMW	MGF
Dep. variable:	*CV*	*SD*	*RANGE*	*CV*	*CV*	*CV*	*CV*	*CV*
Constant	43.60***	45.81	14.19***	50.53***	44.87***	42.92**	31.25	39.16**
AGE: 40	19.70***	12.14***	11.71***	8.51***	9.80***	-0.60	-8.07***	-11.62***
AGE: 55	39.60***	23.94***	23.20***	14.91***	20.49***	5.77*	0.19	-7.66**
AGE: 70	39.28***	23.93***	22.75***	13.75***	18.95***	5.33	1.29	-3.55
OCC: Factory	-16.33***	-10.23***	-9.13***	-0.65	-4.51**	-3.51*	-5.90**	-21.03***
OCC: Computer	-16.38***	-10.26***	-9.15***	-1.43	-4.51**	-3.74**	-7.09***	-22.14***
OCC: Retired	-13.73***	-8.79***	-7.90***	1.59	-2.60	-0.92	-5.55**	-18.29***
SEX: Female	-1.66**	-1.01**	-0.56	2.73***	-1.46***	-0.32	-0.21	-0.57
MARKET	0.24	-0.99***	-0.26	-	-	-	-	-
RETURN	-0.40***	-0.23***	-0.12***	-0.18*	-0.28**	-0.30**	-0.17	-0.90***
COMP	0.23	16.27	0.06	-0.49*	0.32	-0.17	1.22***	-0.04
OPTI	-4.40***	-2.76***	-2.35***	-0.11	-1.48**	-0.53	-1.71**	0.18
OPTC	1.99***	1.08***	0.60***	-	-	-	-	-
RISK	44.57***	29.16***	27.44***	13.54***	8.01*	9.98**	27.48***	-5.09
$RISK^2$	-25.99***	-13.33***	-16.98***	-1.20	-26.62***	-17.39***	-21.27***	-15.19***
EXCESS	-3.25***	-3.46***	0.26	-2.10	-4.41**	-1.20	-6.91***	4.46
F	78.39***	72.86***	63.62***	332.03***	137.96***	47.55***	87.06***	294.49***
R^2	0.69	0.69	0.66	0.92	0.91	0.77	0.87	0.95
Observations	1,313	1,313	1,313	263	263	263	262	262

Notes: OLS estimation across price sets with robust standard errors. Dependent variable measured for each price set as *CV* = coefficient of variation, *SD* = standard deviation and *RANGE* = difference between maximum and minimum price, divided by mean price. All coefficient estimates for *CV* multiplied by 1,000 and those for *SD* by 100. Natural logs taken of premium and excess. *MARKET* and *OPTC* not defined by car type. Firm and month dummies included throughout. Of the 1,320 price sets data were not collected for 7 sets. *** significant at 1% level. ** = 5% and * = 10% level.

Figure 1: Probability Density Functions as *m* Varies for *n* = 7



Note: Evaluation of expression (1) for n = 7 as m varies.

Appendix: The Variance and Mean

Setting $p_1 = 0$ for tractability, then from (3) we have ($p > C$):

$$h(p:m,C,0) = \frac{(p-C)m\exp\{-m(p-C)\}N}{R}.$$

This has a moment-generating function ($t < m$):

$$M(t) = \int_{p=0}^{p=\infty} \frac{(p-C)\ m\ \exp\{(t-m)p + m\ C\}N}{R} dp,$$

which can be evaluated as:

$$M(t) = m\ \exp(m\ C)\left\{\frac{(t-m)\ C+1}{(t-m)^2}\right\}\frac{N}{R}.$$

The first and second derivatives of this are:

$$M'(t) = -m\ \exp(m\ C)\ \left\{\frac{(t-m)C+2}{(t-m)^3}\right\}\frac{N}{R}, \text{ and}$$

$$M''(t) = m\ \exp(m\ C)\ \left\{\frac{2\ (t-m)\ C + 6}{(t-m)^4}\right\}\ \frac{N}{R}.$$

The mean of $h(p:m,C,0)$ is equal to $M'(0)$, so that equation (5) is:

$$\text{mean}h(p:m,\ C,\ 0) \quad = \quad \exp(m\ C)\frac{(2-m\ C)}{m^2}\ \frac{N}{R}. \tag{A1}$$

The variance of $h(p:m,C,0)$ is $M''(0) - M'(0)^2$. Since $M''(0) = \lambda M'(0)$ then (4) is:

$$\text{var}\,h(p:m,C,0) \quad = \quad \text{mean}\ h(p:m,C,0)\,[\lambda - \text{ mean}\ h(p:m,C,0)]. \tag{A2}$$

where equation (6) is:

$$\lambda \equiv \frac{6-2\,m\,C}{m\ (2-m\,C)}. \tag{A3}$$

Differentiating the variance in (A2) with respect to the mean gives $\lambda - 2 \text{ mean } h(p : m)$, which using (A1) and (A3) is positive if and only if:

$$\frac{N}{R} < \frac{m\left(3 - m\,C\right)}{\left(2 - m\,C\right)^2 \exp\left(m\,C\right)}. \tag{A4}$$

To consider this, let ψ denote the right-hand side of (A4) and write $X \equiv m\,C$, so that:

$$\frac{\partial \psi}{\partial X} = \frac{-m\left(2 - X\right)^2 \exp X - m\left(3 - X\right)\left\{-2\left(2 - X\right)\exp X + \left(2 - X\right)^2 \exp X\right\}}{\left(2 - X\right)^4 \left(\exp X\right)^2}. \tag{A5}$$

The right-hand side numerator of (A5) has roots $X = 2 - \sqrt{2}$, 2 and $2 + \sqrt{2}$, but only the first is in the admissible range, $0 < X < 1$. This gives a minimum, so that if (A4) holds for this value of X ($\equiv m\,C$), then it holds for all values of $m\,C$. Substituting $mC = 2 - \sqrt{2}$ into (A4), then after rearrangement a sufficient condition for $\lambda - 2 \text{ mean } h(p : m) > 0$ is:

$$m \quad > \quad \left[\frac{2 \exp\left(2 - \sqrt{2}\right)}{1 + \sqrt{2}}\right] \frac{N}{R}.$$

This is condition (7) of the text.

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