Pricing behaviour under competition in the UK electricity supply industry

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This paper investigates the evolution of electricity prices for domestic customers in the UK following the introduction of competition. The empirical analysis is based on a panel data set containing detailed information about electricity supply prices over the period 1999 to 2006. The analysis examines the pricing patterns and draws inferences concerning the benefits of incumbency and the gains from search. The econometric analysis of persistence and price dispersion provides rather limited support for the view that the market is becoming more competitive and also indicates that there remain significant potential benefits to consumers from searching alternative suppliers.


1. Introduction

On 1st July 2007, EU energy markets became fully open, as a result of Directives 2003/54/EC (electricity) and 2003/55/EC (gas). Amongst other things, this opened European residential markets fully for the first time. The UK government has eagerly embraced the liberalization process. Not only have all UK consumers been able to choose their electricity supplier since May 1999 but around half have done so. Additionally, since March 2002 there has been no supply price regulation. Therefore, an experiment of at least European significance is taking place, concerning the behaviour of consumers and their energy suppliers. As one manifestation of this, US, German, French, and Spanish firms have taken significant stakes in the UK supply industry. What are the effects of this competition on the behaviour of prices?

This paper focuses on the development over time of tariff structures for supply to domestic electricity customers. One null hypothesis is that competition would lead to prices for a product as homogeneous as electricity quickly converging. An alternative is that prices would remain somewhat dispersed, as a consequence
of firms exploiting significant search and switching costs and creating product
differentiation. We investigate this, using a framework that focuses on variables
of interest measuring price dispersion whilst embedding these within a law-of-one-
price (LOOP) model that allows shocks to influence the system.

As background, we should note a number of important institutional features
that facilitate development of competition in the supply market. When the electri-
city market was broken up into generation, transmission, distribution, and supply,
the link between supply and distribution was broken. Transmission and distribu-
tion remain regulated, but any competent potential supplier may obtain a licence.
Thus, by knowing the (regulated) prices for transport, and by writing contracts
for wholesale electricity, a supplier is enabled to design a tariff to attract consumers
away from their incumbent supplier. They can also purchase ancillary services,
such as meter reading, on the market, but suppliers retain responsibility for
billing—a single bill covers all vertical levels. A standardized system of identifying
customers by their meter numbers facilitates their accurate transfer between
suppliers.

As industry regulator, OFGEM is charged with overseeing the development of
competition. Energywatch, a related body, has a duty to provide consumers with
information regarding suppliers. They provided regularly updated price compari-
sion sheets on their website, covering every active supplier, together with comparative
information such as complaints about particular suppliers. Several commercial
companies provide price comparison services, on the basis that they cover the
market and do not favour suppliers selectively. Thus the typical consumer is able
to make an informed choice amongst six or more suppliers. However, all the major
suppliers also engage in their own marketing activity, commonly using a sales
force that moves from door to door within an area. The sales pitch focuses
on price, with a secondary emphasis on service (but in both cases tends to be
untailored and non-specific). Switching activity has been significant: At time
of writing, almost half of all customers are supplied by a supplier that is not
their incumbent.1

The competitors in electricity supply are of three main types. Before liberaliza-
tion, supply was a regionally-based activity, and prices generally differ between the
14 regions still (costs also differ, as a result of transport cost differences).2 Thus one
category of competition comes from suppliers extending their activities across
regions (usually, maintaining a differential in prices). A second category is com-
panies engaged previously in the supply of gas. Prime amongst these is British (in
Scotland, trading as Scottish) Gas, which provided a national integrated service
for the supply of gas, but other gas supply companies, some related to oil

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1 The gross rate of switching is higher, because some people switch back and indeed there is significant ‘churn’.

2 That is, the price you can buy at depends upon your postcode.
companies, also entered the electricity market. The third force is independent suppliers; these have tended not to be companies with a strong knowledge of and reputations for mass market consumer activity or billing.

Our period of analysis runs from February 1999 to December 2006, spanning eight years of price data. During the sample period important strategic and institutional changes in electricity prices have occurred. For example, in April 2002 the energy regulator, OFGEM, removed all price controls for all residential consumers. Furthermore, perhaps as early as the Spring of 2002 a worldwide trend of increasing oil and fuel costs was reflected in substantial increases in fuel costs in the UK. The potential impact of these changes is taken into account in our empirical analysis.

Besides regional differentiation, in particular between in-area and out-of-area customers in the case of the existing electricity supplier, scope exists for companies to differentiate between various broad customer classes. There are three main ways of paying, by (monthly) direct debit, quarterly bill (paid in arrears), or prepayment meter. These involve different supply costs, direct debit being the cheapest and prepayment the most expensive. Since all suppliers’ tariffs are at least two-part, companies can also differentiate between low and high consumers of electricity. There is also a distinction between online-only offerings and more generally available tariffs and latterly, some distinctions relating to contract length; we do not cover these.

We believe our study makes two contributions. First, it adds an important dimension to the literature on the implications of price search. Second, it tracks the effects of opening an important market to competition. It is unique in examining the effect on prices as the market under study is opened to competition, in a context where a complete listing of prices is available on the internet, implying that additional quotes are available to internet users at zero additional charge. Also, shipping costs, which complicate or even bedevil price comparisons in other areas, are always included and ‘bait and switch’ tactics are unlikely. All the tariffs listed have significant consumer numbers using them. Moreover, the product is a significant part of most consumers’ lives, consuming a non-trivial fraction of their income. The savings from shopping around can be, though are not always, considerable.

We develop a framework in Section 2, followed in Section 3 by a description of the data and the econometric procedure. Section 4 contains a discussion of the main results on price spreads and develops interpretations, while Section 5 offers some concluding remarks on the competitive process.

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3 Though the gas market was opened to competition earlier it is less interesting analytically, since it is national not regional in nature, meaning there is less variation to observe. British Gas remains the most important operator.

4 We do not consider at present ‘dual fuel’ deals and the ‘Economy 7’ tariffs (increasingly less important); see Green (2005) on dual fuel.
2. Theoretical framework

UK domestic electricity supply provides an example of a market in which search (and switching) was irrelevant but has now become significant and substantial. What are the implications? Our general strategy in examining observed price movements is to implant into a LOOP empirical framework, considerations suggested as important by search and switching theory.

Farrell and Klemperer’s (2007) core model of switching costs, which assumes firms cannot commit to future prices, is a good fit with our situation. Also, due to regulatory restrictions, firms cannot explicitly discriminate between cohorts of customers. In this case, modelling suggests that some firms specialize in selling to new customers (at low prices) and others in holding on to old customers. New entrant suppliers are likely to shade initial price below marginal cost so as to capture consumers, whom they can later exploit. Switching costs may fall over time, as people get more used to switching, or possibly they may rise, if non-switchers have higher psychic costs of switching than consumers who have already switched.

Turning to search behaviour, given that the good is rather homogeneous, new entrant suppliers into the market must propose lower prices than incumbents in order to capture consumers. Nevertheless, some consumers will choose not to search, staying with their incumbent supplier, or will be reluctant to do so. In the early days of market opening, we may expect some dispersion in pricing between entrant suppliers as they gauge their tactics in the market. As the market matures, if it follows a LOOP, price offerings across the suppliers will move into line, either across entrants as a group, or across both entrants and incumbent.

As long as some consumers are able to search costlessly, models of search cost (Varian, 1980; Stahl, 1989; Sorensen, 2000) predict that as search costs (for the remainder) approach zero then so will the range of prices offered by suppliers. In our context, this relates to costs of searching between entrant suppliers only: Some consumers may decide to remain with their incumbent supplier, but so long as some switch, with negligible search costs it makes no sense for an entrant supplier to offer an uncompetitive deal. Alternatively, if perceived search costs are high or remain significant, or if firms engage in obfuscation regarding their price offer (Ellison and Ellison, 2005), then an entrant may sell supply contracts despite pricing differentially high relative to other entrants.

One factor that has changed over our study period is access to accurate customized information regarding likely bills by means of a broadband internet connection. The National Statistics omnibus survey reports the proportion of consumers connected to the internet rising 38% between March 2001 (the earliest date given) and March 2006, coupled with a rapid movement from dialup to broadband connection. In Varian’s (1980) model, these people are paying a search cost to obtain a complete listing of prices, whilst in Stahl’s (1989) terms, those on broadband can engage in ‘costless’ search (that is, they have no per-firm search cost). Having used one of the comprehensive search engines, and having determined to switch,
they may either switch directly through the internet or by contacting their preferred supplier. Therefore a possible prediction is that the range of prices posted by entrants is reduced over time because of an increase in the proportion of informed consumers or of what Stahl calls ‘shoppers’;\(^5\) though we cannot easily distinguish this effect from a general time effect, they move in the same direction.

One further important factor is the significant reduction in the number of firms in the market over time. Here there are (at least) two forces and predictions depend quite delicately upon the nature of the model (see Janssen and Moraga-González, 2004). Consider the position as firms enter in a Stahl-type model. The ‘business stealing’ effect of charging lower prices to capture more consumers strengthens, but so too does the ‘surplus appropriation’ effect of earning a high surplus from uninformed consumers. Eventually as the number of firms becomes very large, the market becomes less competitive. Morgan et al. (2006) find that as the number of firms increases, informed customers pay lower prices whilst the uninformed face higher prices. Barron et al. (2004) consider a broad range of models and show that, dependent upon the nature of the underlying model, the number of sellers and average price can be either negatively or positively correlated and, in addition, the number of sellers and price dispersion can be either positively or negatively correlated! Clearly, the impact of changing firm numbers is one that will only be settled empirically.

To summarize, models of search and switching behaviour suggest some tendencies, but are notably short on crisp predictions.\(^6\) Hence we view our empirical analysis as a descriptive investigation of the impact of search and switching costs in the market over time, guided by theory. Over time, actual price differentials move around, as example graphs later show. To uncover underlying trends, we employ a technique used in international trade analyses of the LOOP. Indeed, our econometric analysis has some parallels with Goldberg and Verboven’s (2005) investigation of car pricing across European countries, which employs a similar econometric model to examine whether harmonization policies, such as adoption of the Euro, have led to increasing closeness of car price movements across the countries involved. This technique allows us to uncover the underlying speed of adjustment of price differences to shocks (e.g. cost shocks) and at the same time to check that the observed movements are not just random. In our case, the null conjecture is that harmonization towards a LOOP takes place naturally over time, as consumers become more aware of their options and gain experience (directly or through word of mouth), firms seek to gain customers, or events such as real price increases trigger search behaviour. It may however proceed

\(^5\) Tight predictions relating the proportion of ‘shoppers’ to the distribution of prices are surprisingly difficult to generate—see Janssen and Moraga-Gonzalez (2004). A general difficulty is that the price distributions suggested by search cost models are characterized by pdfs in which most weight is in the tails, so they are not easily summarized in the normal way by standard deviations, etc.

\(^6\) Recently, Chandra and Tappata (2008) have emphasized how theory suggests that many of the relationships examined in this area are fundamentally non-monotonic.
at different speeds across different consumer types, for example different payment methods (see Section 3.1 below), due to the different search and switching costs consumers face. Our empirical strategy enables us to examine this possibility.

We develop four different indexes which measure price dispersion between incumbent and entrants and across entrants. We model the evolution of these indexes over time using a LOOP model and test gradual convergence to the relative version of the LOOP across different products and geographical regions by testing for significant changes in average price differentials. We examine price dispersion across entrant suppliers, capturing the impact of search costs, through two measures, both relating solely to entrant firms. These are HL, the difference between the highest and lowest price available from entrant firms, and ML, the difference between the median entrant’s price and the lowest. If search costs are falling, and obfuscation does not increase, we would expect both to shrink over time. HL is of independent interest, showing the potential impact on a consumer of getting the choice very wrong.7

We pick as our measure of the impact of switching costs the difference between the price charged by the incumbent and the price charged by the median entrant (difference IM). This captures as nearly as possible the pure advantage to an incumbent seller over an entrant. If HL, ML, and IM do not shrink over time, this is evidence of limited competition, however much switching occurs. For completeness, we also report on the magnitude IL, the difference between the incumbent price and the lowest entrant offering, namely the maximum gain available to a consumer from search and switching activity.8

Customers who purchase over the internet (particularly since around the beginning of 2006; OFGEM, 2007) may avail themselves of online-only offers.9 Our data source is unlikely to capture all these internet-only tariffs. Hence for consistency we only examine magnitudes generated using prices available through conventional means. Offers obtained through internet searches may nevertheless have an influence on non-internet-only prices.

3. Data and econometric procedure
3.1 Data
Our analysis of the changes in electricity retail prices since the introduction of competition takes into account geographical, product market and temporal dimensions. We have a balanced panel of 48 bimonthly price observations for each firm

7 All our prices are ‘real’ in the sense that some group of consumers are paying them. We estimate that the most popular tariff in our sample has around one million consumers, whilst the least popular has over 3,000 users.
8 For reasons discussed in a companion paper (Giulietti et al., 2008), we decide against relating any of these measures to cost magnitudes.
9 By March 2006, only approximately 4% of consumers were signed up to online tariffs, but the number was increasing rapidly.
in the market over the period February 1999 to December 2006. Our pricing data were obtained from the Consumers’ Association website initially and, later, from the successor OFGEM and Energywatch websites. All price offers by suppliers are public, in this sector.

The data also reveal the number of active firms for each bill type; the number operating ranges from 18 to six suppliers over time. All the independent firms who initially entered have now effectively vanished, whilst there has been significant consolidation amongst the remainder, so that we are left with six significant, (to a greater or lesser extent) vertically integrated, players and little prospect of further entry. Table 1 gives some basic information on the industry, largely culled from various OFGEM reports. Unfortunately, consistent frequent detailed data on market shares is not publicly available. The overall market shares of the big six have remained quite stable for the past four years, having previously increased significantly due to market consolidation. Partly driven by price rebalancing, there has been a secular move away from prepayment and standard credit tariffs to direct debit arrangements.

Since electricity retail prices for domestic consumption in the UK differ by payment method and geographical location, our data set comprises 84 cross-sectional units corresponding to the 14 supply regions, three payment methods namely direct debit (DD), quarterly bills (QB), and prepayment meters (PP), and two levels of consumption, namely ‘high’ and ‘low’. We distinguish between high (4950 KWh per year) and low (1650 KWh per year) consumption

Table 1 Market evolution (2000–2007)

<table>
<thead>
<tr>
<th>Market shares (%)</th>
<th>2000</th>
<th>2003</th>
<th>2005</th>
<th>2007</th>
</tr>
</thead>
<tbody>
<tr>
<td>BG</td>
<td>14</td>
<td>23</td>
<td>22</td>
<td>21</td>
</tr>
<tr>
<td>Powergen</td>
<td>8</td>
<td>22</td>
<td>21</td>
<td>19</td>
</tr>
<tr>
<td>Npower</td>
<td>8</td>
<td>16</td>
<td>15</td>
<td>16</td>
</tr>
<tr>
<td>EDF</td>
<td>10</td>
<td>15</td>
<td>13</td>
<td>14</td>
</tr>
<tr>
<td>Scottish and Southern</td>
<td>14</td>
<td>14</td>
<td>16</td>
<td>18</td>
</tr>
<tr>
<td>Scottish Power</td>
<td>10</td>
<td>10</td>
<td>13</td>
<td>12</td>
</tr>
<tr>
<td>Others</td>
<td>36</td>
<td>&lt;1</td>
<td>&lt;1</td>
<td>&lt;1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Payment method (%)</th>
<th>2000</th>
<th>2003</th>
<th>2005</th>
<th>2007</th>
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<tr>
<td>Direct debit</td>
<td>37</td>
<td>43</td>
<td>45</td>
<td>47</td>
</tr>
<tr>
<td>Standard credit</td>
<td>46</td>
<td>42</td>
<td>41</td>
<td>40</td>
</tr>
<tr>
<td>Prepayment</td>
<td>17</td>
<td>15</td>
<td>14</td>
<td>13</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Switchers by payment method (%)</th>
<th>2000</th>
<th>2003</th>
<th>2005</th>
<th>2007</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direct debit</td>
<td>22</td>
<td>46</td>
<td>55</td>
<td>59</td>
</tr>
<tr>
<td>Standard credit</td>
<td>15</td>
<td>34</td>
<td>36</td>
<td>45</td>
</tr>
<tr>
<td>Prepayment</td>
<td>6</td>
<td>33</td>
<td>41</td>
<td>47</td>
</tr>
</tbody>
</table>

Source: Ofgem, various reports and BERR, Energy statistics.
in order to reflect the at least two-part nature of electricity tariffs. This allows us to consider six different product prices set by residential energy suppliers. All the companies and all the tariffs they offered (excluding internet-only tariffs) are used in the calculation of the variables ML, HL, IM, and IL. Our ‘prices’ are average yearly bills for customers on low and high consumption levels for each of the main payment methods, excluding internet-only tariffs.

Some sample illustrative charts are shown in Figs 1 to 3, based on national data. The price pattern observed at regional level is similar. Although these charts all relate to direct debit consumers, they are enough to suggest that a simple pattern of convergence to a single price does not exist. Moreover, they imply that we first need to examine whether a deterministic trend can legitimately be identified.

3.2 Stationarity

Empirical tests of price convergence (what we refer to as stationarity) are common in the international trade area (Frankel and Rose, 1996), but also elsewhere (Cecchetti et al., 2002; Goldberg and Verboven, 2005), using formulae rather like (1) below.

Whilst unit root tests applied to single series suffer from low power, panel unit root techniques offer potentially enhanced test power. In this paper we

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10 Results including these tariffs can be found in our working paper Giulietti et al. (2007).
follow Hadri (2000), who proposes residual-based Lagrange Multiplier tests for the null hypothesis that all the time series in the panel are stationary (either around a level or a deterministic time trend), against the alternative that some of the series are non-stationary. The key advantage is that it is possible to conclude that all series in the panel are stationary, if the null hypothesis is not rejected. To compute the
Hadri tests, which are panel versions of the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) (1992) tests, let \( \hat{e}_{it} \) be the residuals from the regression of \( y_{it} \) on an intercept, when testing stationarity around a level (or on an intercept and a linear trend term, when testing stationarity around a deterministic time trend). Then, the individual KPSS stationarity test is given by:

\[
\eta_{i,T} = \frac{\sum_{t=1}^{T} S_{it}^2}{T^2 \hat{\sigma}_{\hat{e}}^2},
\]

\( S_{it} \) denotes the partial sum process of the residuals given by \( S_{it} = \sum_{j=1}^{t} \hat{e}_{ij} \), and \( \hat{\sigma}_{\hat{e}}^2 \) is a consistent estimator of the long-run variance of \( \hat{e}_{it} \) from the appropriate regression. KPSS (1992) propose a nonparametric estimator of \( \hat{\sigma}_{\hat{e}}^2 \) based on a Bartlett window having a truncation lag parameter of \( l_q = \text{integer}[q(T/100)^{1/4}] \), with \( q = 4,12 \). Because such stationarity tests exhibit very low power after correcting for size distortions (Caner and Kilian, 2001), we follow Sul et al. (2005), who propose a boundary condition rule for \( \hat{\sigma}_{\hat{e}}^2 \) that improves the size and power properties of the KPSS stationarity tests.\(^{11}\)

The Hadri (2000) panel stationarity test statistic is given by the simple average of individual univariate KPSS stationarity tests which, after a suitable standardization, using appropriate moments, follows a standard normal limiting distribution.\(^{12}\) However, a critical assumption underlying the Hadri tests is cross-section independence, which we cannot assume here. Moreover, Giulietti et al. (2009) show that even for relatively large \( T \) and \( N \) the tests suffer from severe size distortions in the presence of cross-sectional dependence. To overcome this, we apply Giulietti et al.’s (2009) bootstrap method, which leads to Hadri tests that are approximately correctly sized. The details of the bootstrap can be found e.g. in Hadri and Rao (2008). Our results are based on 2,000 bootstrap replications.

An important institutional change in price setting was introduced in April 2002, when the energy regulator, OFGEM, removed all price controls for residential consumers. Furthermore, starting from Spring 2002 we observe a substantial increase in fuel costs as illustrated in Fig. 4. To allow for the potential impact of these changes on our empirical analysis, the dataset is split into two periods—before and after April 2002. Applying the Hadri tests for panel stationarity to our dataset over each sample period, we find that all the series analysed are stationary around a trend, as reported in Table 2. Given this result, we now turn our attention to the trends in price spreads.

\(^{11}\) Additional Monte Carlo evidence reported by Carrion-i-Silvestre and Sansó (2006) also indicates that the proposal in Sul et al. (2005) is to be preferred since the KPSS statistics exhibit less size distortion and reasonable power.

\(^{12}\) Asymptotic moments can be found in Hadri (2000) while finite sample critical values appear in Hadri and Larsson (2005).
3.3 Econometric approach to the main question

Our four estimating equations have the following form:

\[ \Delta Y_{r p c, t} = \alpha_0 + \alpha_{1 r p c} Tr + \beta Y_{r p c, t-1} + \sum_{k=1}^{K} \gamma_k \Delta Y_{r p c, t-k} + \delta NFIRMS_{r, t} + \epsilon_{r p c, t} \]  

(1)

where \( Y \) refers to the variables ML, HL, IM, IL, being the price spread variables discussed in Section 2 expressed as percentages. The subscripts \( r, p, c, \) and \( t \) identify
a region, product, consumption level, and time period, respectively. $\Delta$ indicates the first difference operator, so that $\Delta Y_{rpc,t} = Y_{rpc,t} - Y_{rpc,t-1}$. Equation (1) can be reformulated to obtain an equivalent expression in levels by adding $Y_{rpc,t-1}$ to both sides of the equation:

$$Y_{rpc,t} = \alpha_0 + \alpha_{1rpc}Tr + \beta Y_{rpc,t-1} + \sum_{k=1}^{K} \gamma_k \Delta Y_{rpc,t-k} + \delta NFRMS_{r,t} + \varepsilon_{rpc,t}$$

(2)

Assuming the coefficient $\beta$ is negative and significant then the price sequence will be stationary (around a trend). The value $\beta$ provides an indication of the speed of convergence to the long-run equilibrium when exogenous shocks are observed, the alternative hypothesis being persistence of price differential once a deviation from the long-run equilibrium takes place. The coefficient $\alpha_0$ captures product- and region-specific fixed effects, with the average level of price dispersion being $-\alpha_0/\beta$, in each of our four indexes, over our sample period. These differentials can be driven by a series of factors such as different marketing costs or service quality and partly by mark-up differences and incumbency advantage in different regions.

Of more significance, the coefficients $\alpha_{1rpc}$ on trends capture the underlying trends in price differentials over time (again scaled by $-\beta$). The null hypothesis is that $\alpha_{1rpc}$ is zero. But on the assumption that liberalization processes increase competitive price pressure due to increased consumer search, penalizing higher-priced entrants and/or by erosion of incumbency advantage against entrants through switching, we would expect trends to be downward. They enable us to investigate the presence, or absence, of convergence in the sense discussed in Section 2. A significant positive (negative) deterministic trend term would provide evidence in support of an increasing (decreasing) gap or range (ML or HL) in average bills over time for the relevant region, product and consumption level, reflecting the underlying evolution of consumers’ search costs as a result of competition. A deterministic trend in the bill differentials between the median or lowest-priced entrant firm and the incumbent (IM or IL) examines the evolution of customers’ switching costs in this market. The coefficient $\delta$ picks up the effects of changing firm numbers, so controlling for the effects of changes in market structure and the nature of competition as firms enter or exit the market.

13 We initially incorporated different constants for regions, products, etc, but tests showed a single constant term to be an acceptable simplification.

14 Alternative approaches to test price dispersion in the presence of search costs, applying maximum likelihood estimation techniques on price data alone, have been considered recently by Hong and Shum (2006) and Moraga-González and Wildenbeest (2006).
The first $K$ differences in the lagged dependent variable are included on the right hand side to account for potential serial correlation in the error term. The inclusion of five lags of these first differences reduces the number of available bimonthly observations to be used for estimation to 42, so that the total number of observations available is $3528 (T = 42, n = 84)$, 1512 of which are used for the first sample period estimation (February 1999 to April 2002), with the remaining 2016 observations used for the second sample period (June 2002 to December 2006). Finally, $e$ is the error term.

All equations are estimated using the Least Squares Dummy Variable estimator. Although biased but consistent based on a RMSE criterion, this estimator has been shown to perform as well as alternative procedures for balanced panels of dimensions close to ours; see the Monte Carlo simulation results in Judson and Owen (1999). The estimated $t$-statistics are based on White’s heteroskedasticity-consistent standard errors and covariances.

4. Results and interpretation
4.1 Discussion of results
Our empirical analysis starts with fairly general specifications of eq. (1) explaining price dynamics. This allows us to distinguish between movements of electricity prices across geographical, payment method and consumption level dimensions. In order to account for all possible sources of cross-sectional variation in the trend we considered all possible interactions between the different cross-sectional dimensions. The interaction coefficients between the time trend and fixed effects give an indication of the increases or decreases in our indexes of price dispersion over time.

We refer to the most general specification as the unrestricted model. Based on results from the stationarity tests reported in Table 2, the unrestricted model is estimated over two sample periods, before and after June 2002. Splitting the sample period in this way allows us to deal with stationary series at the same time as accounting for the potential effect of exogenous changes arising from market pressures and institutional changes mentioned earlier.

To assess variability across the fourteen electricity regions, we performed a series of Wald tests on the estimated coefficients from the unrestricted models with results reported in Table 3. It is clear that for dependent variable IL no real simplification is possible, but that in the other three cases (ML, HL, IM) the model can be simplified. For these, independently of the sample period, for low consumption...
users we observe no statistically significant regional differences across the tariffs for all payment methods (see Table 3, lines 4 to 6, 8, 13 to 15, and 17). Furthermore, for the sample period until April 2002 we cannot reject the hypothesis that the estimated coefficients are not significantly different between tariffs for high and low consumption levels (line 9) for any payment method. The corresponding hypothesis for the second sample period is rejected, at least at the 10% significance level (line 18). In the second sample period, Wald tests reveal regional variations in the estimated coefficients for IL and IM but not for ML and HL (lines 10 to 12) for high consumption users.

Because the set of full results is so extensive, with broad support from the hypothesis tests in Table 3, it is useful to examine a restricted version of the model where the distinction between high and low consumption levels is suppressed. Results for the full model can be examined in the online Appendix, at Appendix 1. The chosen restricted specification is such that all the dependent variables bar IL are regressed on the same set of regressors. The results from these for the two sample periods ‘Before’ and ‘After’ April 2002 are reported in Table 4. There is considerable concordance on the results within periods.

Table 3 Unrestricted model: tests of hypotheses

<table>
<thead>
<tr>
<th>Sample period</th>
<th>Dependent variable</th>
<th>AML</th>
<th>AHL</th>
<th>AIM</th>
<th>AIL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feb. 1999–Apr. 2002</td>
<td>1. DD high (Group 1)</td>
<td>3.36 (0.00)</td>
<td>0.44 (0.96)</td>
<td>0.56 (0.89)</td>
<td>4.87 (0.00)</td>
</tr>
<tr>
<td></td>
<td>2. PP high (Group 2)</td>
<td>2.50 (0.00)</td>
<td>1.41 (0.15)</td>
<td>3.75 (0.00)</td>
<td>2.48 (0.00)</td>
</tr>
<tr>
<td></td>
<td>3. QB high (Group 3)</td>
<td>2.10 (0.01)</td>
<td>0.53 (0.91)</td>
<td>0.79 (0.67)</td>
<td>3.94 (0.00)</td>
</tr>
<tr>
<td></td>
<td>4. DD low (Group 4)</td>
<td>1.09 (0.37)</td>
<td>0.48 (0.94)</td>
<td>0.95 (0.50)</td>
<td>2.83 (0.00)</td>
</tr>
<tr>
<td></td>
<td>5. PP low (Group 5)</td>
<td>1.35 (0.18)</td>
<td>0.85 (0.61)</td>
<td>0.44 (0.95)</td>
<td>2.06 (0.01)</td>
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<td>6. QB low (Group 6)</td>
<td>1.03 (0.41)</td>
<td>0.34 (0.99)</td>
<td>0.96 (0.49)</td>
<td>2.41 (0.00)</td>
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<td>7. DD high = PP high = QB high</td>
<td>1.62 (0.01)</td>
<td>0.76 (0.87)</td>
<td>1.39 (0.05)</td>
<td>2.82 (0.00)</td>
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<td>8. DD low = PP low = QB low</td>
<td>0.91 (0.63)</td>
<td>1.13 (0.27)</td>
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<td>9. DD low = PP low = QB low = 0</td>
<td>0.90 (0.65)</td>
<td>1.11 (0.29)</td>
<td>0.66 (0.95)</td>
<td>2.59 (0.00)</td>
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<td>Jun. 2002–Dec. 2006</td>
<td>10. DD high (Group 1)</td>
<td>0.69 (0.78)</td>
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<td>5.55 (0.00)</td>
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<td>11. PP high (Group 2)</td>
<td>1.16 (0.31)</td>
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<td>4.82 (0.00)</td>
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<td>12. QB high (Group 3)</td>
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<td>14. PP low (Group 5)</td>
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<td>0.46 (0.95)</td>
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<td>15. QB low (Group 6)</td>
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<td>0.69 (0.77)</td>
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<td>16. DD high = PP high = QB high</td>
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<td>2.85 (0.00)</td>
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<td>17. DD low = PP low = QB low</td>
<td>0.97 (0.52)</td>
<td>0.98 (0.52)</td>
<td>1.08 (0.34)</td>
<td>0.86 (0.73)</td>
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<td>18. DD low = PP low = QB low = 0</td>
<td>1.34 (0.07)</td>
<td>1.44 (0.03)</td>
<td>1.69 (0.00)</td>
<td>1.09 (0.32)</td>
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</tbody>
</table>

Notes: The tests of hypotheses refer to Wald tests that test whether the estimated coefficients associated to the variables within a group (as defined in the Table of Appendix 1) are statistically the same. In lines 9 and 18, the hypotheses refer to whether the estimated coefficients in the relevant groups are all equal to zero. The tests are reported in their F-version, with probability values in parentheses.
<table>
<thead>
<tr>
<th>Regressors</th>
<th>$\Delta Y = \Delta ML$</th>
<th>$\Delta Y = \Delta HL$</th>
<th>$\Delta Y = \Delta IM$</th>
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<td>After</td>
<td>Before</td>
</tr>
<tr>
<td></td>
<td>Coef.  t-stat</td>
<td>Coef.  t-stat</td>
<td>Coef.  t-stat</td>
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<td>$Y(-1)$</td>
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<td>$-0.17$ $-6.24$</td>
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<td>NFIRMS</td>
<td>$0.09$ $1.59$</td>
<td>$0.59$ $6.18$</td>
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</table>

**Group 1**

- $\text{Tr*EA*DD}$: $-0.09$ $-3.24$ $0.08$ $3.96$
- $\text{Tr*EM*DD}$: $-0.08$ $-2.51$ $0.10$ $4.59$
- $\text{Tr*LD*DD}$: $-0.04$ $-1.04$ $0.10$ $4.66$
- $\text{Tr*MD*DD}$: $-0.07$ $-2.06$ $0.08$ $3.49$
- $\text{Tr*MW*DD}$: $-0.09$ $-4.00$ $0.07$ $3.16$
- $\text{Tr*NT*DD}$: $-0.01$ $-0.22$ $0.08$ $3.88$
- $\text{Tr*NW*DD}$: $-0.09$ $-3.30$ $0.08$ $3.76$
- $\text{Tr*SE*DD}$: $-0.06$ $-1.31$ $0.11$ $4.40$
- $\text{Tr*SH*DD}$: $-0.06$ $-2.53$ $0.08$ $3.46$
- $\text{Tr*SP*DD}$: $-0.09$ $-3.67$ $0.11$ $4.02$
- $\text{Tr*ST*DD}$: $-0.07$ $-2.46$ $0.11$ $4.85$
- $\text{Tr*SA*DD}$: $-0.07$ $-2.57$ $0.08$ $4.10$
- $\text{Tr*SW*DD}$: $-0.11$ $-4.37$ $0.10$ $4.98$
- $\text{Tr*YK*DD}$: $-0.04$ $-1.45$ $0.09$ $3.89$

**Group 2**

- $\text{Tr*EA*PP}$: $-0.01$ $-0.40$ $0.12$ $5.22$
- $\text{Tr*EM*PP}$: $0.00$ $0.05$ $0.14$ $5.37$
- $\text{Tr*LD*PP}$: $-0.01$ $-0.41$ $0.13$ $4.84$
- $\text{Tr*MD*PP}$: $-0.02$ $-0.77$ $0.12$ $5.51$

(continued)
Table 4 Continued

<table>
<thead>
<tr>
<th>Regressors</th>
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<th>$\Delta Y = \Delta HL$</th>
<th>$\Delta Y = \Delta IM$</th>
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<td>t-stat</td>
<td>Coef.</td>
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<tr>
<td>Tr<em>NT</em>PP</td>
<td>0.04</td>
<td>1.23</td>
<td>0.14</td>
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<td>Tr<em>NW</em>PP</td>
<td>0.04</td>
<td>1.16</td>
<td>0.16</td>
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<td>Tr<em>SE</em>PP</td>
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<tr>
<td>Tr<em>SH</em>PP</td>
<td>-0.07</td>
<td>-2.94</td>
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<td>Tr<em>ST</em>PP</td>
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<td>Tr<em>SA</em>PP</td>
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<td>0.12</td>
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<tr>
<td>Tr<em>SW</em>PP</td>
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<td>-0.02</td>
<td>0.13</td>
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<td>Tr<em>YK</em>PP</td>
<td>0.05</td>
<td>1.42</td>
<td>0.14</td>
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Group 3

| Tr*EA*QB  | -0.12 | -3.26  | 0.12  | 4.76   | -0.24 | -4.38  | 0.36  | 8.42   | 0.05  | 1.93   | -0.05 | -2.04  |
| Tr*EM*QB  | -0.07 | -1.97  | 0.12  | 4.84   | -0.18 | -3.08  | 0.35  | 8.70   | 0.03  | 1.27   | -0.05 | -2.04  |
| Tr*LD*QB  | -0.06 | -1.84  | 0.14  | 5.27   | -0.17 | -3.31  | 0.34  | 7.86   | 0.04  | 2.00   | -0.09 | -3.26  |
| Tr*MD*QB  | -0.05 | -1.47  | 0.12  | 5.14   | -0.18 | -3.44  | 0.34  | 8.44   | 0.01  | 0.44   | -0.05 | -2.09  |
| Tr*MW*QB  | -0.09 | -3.45  | 0.10  | 3.86   | -0.20 | -4.05  | 0.32  | 8.19   | 0.04  | 1.95   | -0.06 | -2.59  |
| Tr*NT*QB  | 0.02  | 0.50   | 0.13  | 5.53   | -0.09 | -1.49  | 0.34  | 8.32   | 0.05  | 2.20   | -0.04 | -1.86  |
| Tr*NW*QB  | -0.08 | -3.15  | 0.10  | 4.40   | -0.22 | -5.03  | 0.37  | 7.48   | 0.05  | 2.14   | -0.05 | -1.79  |
| Tr*SE*QB  | -0.05 | -1.28  | 0.14  | 5.40   | -0.18 | -3.20  | 0.35  | 7.57   | 0.03  | 1.35   | -0.08 | -3.17  |
| Tr*SH*QB  | -0.10 | -4.07  | 0.10  | 3.94   | -0.19 | -3.94  | 0.32  | 8.28   | 0.07  | 2.66   | -0.11 | -3.95  |
| Tr*SP*QB  | -0.12 | -4.80  | 0.12  | 4.17   | -0.21 | -4.38  | 0.34  | 8.29   | 0.07  | 2.43   | -0.07 | -2.58  |
| Tr*ST*QB  | -0.08 | -2.70  | 0.10  | 4.46   | -0.19 | -4.11  | 0.33  | 7.98   | 0.08  | 3.07   | -0.09 | -3.58  |
| Tr*SA*QB  | -0.06 | -1.38  | 0.09  | 4.08   | -0.19 | -3.16  | 0.32  | 8.55   | 0.05  | 2.23   | -0.11 | -4.26  |
Table 4 Continued

<table>
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<th>$ΔY = ΔIM$</th>
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<td>After</td>
<td>Before</td>
</tr>
<tr>
<td>Tr<em>SW</em>QB</td>
<td>-0.11</td>
<td>-3.20</td>
<td>0.11</td>
</tr>
<tr>
<td>Tr<em>YK</em>QB</td>
<td>-0.03</td>
<td>-0.81</td>
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Tests of hypotheses

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<th>Coef. (t-stat)</th>
<th>Coef. (t-stat)</th>
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<td>0.27 (1.00)</td>
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<td>Group 2</td>
<td>2.32 (0.00)</td>
<td>1.43 (0.14)</td>
<td>1.55 (0.09)</td>
<td>1.06 (0.39)</td>
</tr>
<tr>
<td>Group 3</td>
<td>1.68 (0.06)</td>
<td>1.24 (0.24)</td>
<td>0.59 (0.86)</td>
<td>0.42 (0.96)</td>
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</tbody>
</table>

Regressors

<table>
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<th>$ΔY = ΔHL$</th>
<th>$ΔY = ΔIM$</th>
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<tr>
<td>R-squared</td>
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<td>0.13</td>
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<tr>
<td>Adjusted R-squared</td>
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<td>0.24</td>
<td>0.10</td>
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<tr>
<td>S.E. of regression</td>
<td>2.64</td>
<td>3.40</td>
<td>5.38</td>
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<tr>
<td>F-statistic [p-value]</td>
<td>5.49 [0.00]</td>
<td>14.12 [0.00]</td>
<td>4.37 [0.00]</td>
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<tr>
<td>Significant trends</td>
<td>48%</td>
<td>100%</td>
<td>64%</td>
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</tbody>
</table>

Notes: The regressions include five lags of the dependent variable to account for potential serial correlation; also regional dummies for Eastern (EA), East Midlands (EM), London (LD), Midlands (MD), Manweb (Merseyside and North Wales) (MW), Northern (NT), North Western (NW), South Eastern (SE), Scottish Hydro (Northern Scotland) (SH), Scottish Power (Southern Scotland) (SP), Southern (ST), South Wales (SA), South West (SW), and Yorkshire (YK); product dummies for Direct Debit (DD), Quarterly Bills (QB) and Prepayment Meter (PP); and consumption dummies for low consumption levels (L). Tr denotes a linear trend (rising bimonthly). t-statistics are based on White heteroskedasticity-consistent variance-covariance matrix. The ‘tests of hypotheses’ refer to Wald tests on whether the estimated coefficients associated with variables within a group are statistically the same. They are reported in their F-version, probability values in parentheses. ‘Significant trends’ is the percentage of significant trend interaction coefficients statistically significant at the 5% level.
Table 4’s results for the first period indicate almost entirely negative and commonly statistically significant trend coefficients for both ML and HL across regions for DD and QB bill types, but not for PP. In quantitative terms, taking point estimates for Eastern region for Direct Debit customers (row 1 of group 1), ML declines by \((0.09/0.27) (\alpha/\beta)\) per two-month period, or around two percentage points per annum. On the other hand, the variable related to incumbency advantage (IM) shows a positive and mostly statistically significant trend across regions and payment methods \((0.05/0.08\) or nearly four percentage points annually using the same example). Given the early stage of the market, these results are consistent with search costs falling in the first period, but with switching costs rising, perhaps because those consumers who were switching were increasingly reluctant switchers. Also in the case of prepayment, where consumers might find it more difficult to change supplier, there is no clear trend towards reduced dispersion and, at least in the first period, it behaves statistically differently from other payment methods, consistent with Table 1’s switching figures.

The second period results show that the negative trend in ML and HL turns positive and statistically significant across all regions and payment methods, while the positive trend in incumbency advantage becomes (slightly) negative and commonly statistically significant across regions and payment methods. It is difficult to imagine search costs are increasing, one possible implication of the first finding. More likely is either that suppliers have become more successful at differentiating their products from other suppliers, so the search has less of a commodity nature, or that entrant firms have regard not only to capturing new customers but increasingly also to retaining, or even milking, those gained. The result that incumbency advantage is shrinking may arise either because consumers are becoming more used to switching, or because past price hikes emanating from cost increases mean greater absolute money amounts are at stake so prompting more switching, or finally, because incumbents wish to regain some of the consumers they have lost, or slow their departure. We discuss in Section 4.2 the ramifications of later switches being not solely from incumbent to an entrant.

The upshot of these various factors is that in neither sub-sample do we observe the trend decline in price dispersion across different firms which might be predicted to result from the liberalization process and the pressure put on firms by consumers exercising their choice. To illustrate, consider the increased gap between the incumbent and the lowest priced entrant (IL), where the trend is positive not negative across both periods, for higher consumption and, in most regions, also for low consumption. Using as an example DD for Eastern, high consumption, this gap is increasing at over 2.6 annual percentage points in the first period, almost two in the second period.

The general trend in the price indexes is also partly reflected in the estimated effect of market structural changes, measured by the number of firms operating in the market. Throughout the period under examination, (non-incumbent) firm numbers have been declining regularly. The obvious interpretation of the estimated positive coefficients on the ‘number of firms’ variable for ML and HL over both
sample periods is that as the number of firms reduces, search costs decline. The positive association with dispersion is broadly consistent with Morgan et al. (2006). However for the second part of the sample only we estimate a significantly negative coefficient on firm numbers for IM.

Because the time trend variable obviously rises over time, whilst the firm numbers variable declines, it is a little difficult to disentangle the dependent variables’ evolutions over time using our estimates. To clarify this issue, we extrapolated our model out by six months whilst reducing the number of active firms from six to five. The extrapolated values suggest a decline in the price gaps IM and IL, whilst they imply an increase in ML (except for Direct Debit) and HL. Detailed figures for this simulation are reported in Table 5.

What about speed of adjustment to shocks? The β coefficients, all of which are negative and statistically different from zero, imply that the variables analysed are trend stationary processes. Speed of adjustment to exogenous shocks or innovations was computed from the impulse response functions for each separate series.17 Our results18 indicate that the speed of adjustment in the first period has an average half life across 84 series ranging from 10 to 6 months, with HL showing the fastest adjustment. The second period speed of adjustment is slightly slower, with the estimated half life ranging from 12 to eight months, IM showing the fastest adjustment.

Finally, we should consider two possible caveats relating to the development of the market. One development, which has captured a significant proportion of switching consumers, is a ‘dual fuel’ type of tariff where the parties contract for consumer requirements of both electricity and gas to come from the same supplier.19 Broadly, the results for relevant magnitudes on dual fuel show substantial similarities with those we report in detail here; in particular there is no tendency for them to shrink. Appendix 2 discusses the issue in somewhat more detail. The other recent development is more complex contracts (e.g. prices fixed for a period), largely available through internet purchase. We exclude such contracts from the analysis undertaken here, but our results incorporating what information we have on internet tariffs are essentially unchanged.

4.2 Some interpretations
The results on price trends over time are clearly unable to support a naïve Bertrand-type explanation for the price differences experienced in this industry—prices are

17 The estimated value of β can be used to calculate the approximate half-life of a shock on the dependent variable based on the formula – ln(2)/β only for simple AR(1) processes. For more complicated processes impulse response functions should be preferred.

18 These results are not reported here due to space limitations but are available from the authors on request.

19 Prepayment customers are not eligible for dual-fuel tariffs. Moreover, the 20% of customers who have no gas cannot use these tariffs. Altogether around 2/3 of consumers could choose them.
not converging to a single value or LOOP. Rather, they demonstrate a continuing incumbency advantage in line with the general prediction of switching cost models, although not a more specific prediction of declining gap between the incumbent and lowest available price (IL).

The less straightforward finding is the range of prices across entrant firms within an area. Here the first issue to consider is whether price patterns relate to a Varian/Stahl-type mixed strategy equilibrium. The basic prediction of the several mixed strategy variants, a \textit{ceteris paribus} positive relationship between the number of firms and the spread of prices, is borne out by the results shown in Table 4. In addition, the evidence on price spreads over time more generally is consistent with the mixed strategy explanation.

To examine this more closely, we follow Lach (2002) in taking various cuts of the data. First, we examine the proportion of time for which entrant firms’ prices are above or below their median value.\(^{20}\) The details are reported in Appendix 3. Summarizing briefly, it is remarkably seldom that a firm is a ‘good’ or ‘bad’ buy

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\(^{20}\) Lach considered \textit{inter alia} the identity of firms occupying quartiles of the price distribution. With only six players at the end of our period, this would clearly be inappropriate.
over the period—the clearest message from the table is that firms spend time in both positions. To gain a more quantitative impression, again following Lach, we calculated Spearman rank correlations between February 1999 price and price at time \( t \) based on the price ranks of the six companies that survived over the whole period: British Gas, PowerGen, Npower, London (EDF), Scottish and Southern, and Scottish Power.\(^{21}\) The critical value is 0.771 at 5% significance level (Gibbons and Chakraborti, 1992, Table M). Taking as an example the East Midlands region, low or high consumption, with payment by direct debit, our results identify no significant correlation beyond a period of one year for low consumption, and six months for high consumption. In sum, there is little evidence that price advantages for one firm persist for long periods, rather the prices appear to follow a pattern consistent with mixed strategy equilibrium.\(^{22}\)

It is commonly found (for example in Sorensen, 2000) that as the proportion of customers who become well informed increases, the spread of prices decreases. The positive trend in HL in the second period goes against this common view, though is consistent with Chandra and Tappata (2008), and may mean that a pure search cost explanation for the observed pricing patterns across entrants is incomplete in this case.

A plausible missing element is that this is a market where considerable re-switching takes place. For example, of the 4.5 million total switches in 2005 only 38.6% were from incumbent to an entrant. Nearly 40% were churn amongst entrants and 22.7% of switchers actually returned to their incumbent! (OFGEM, 2006) In this context, an entrant player will trade off a number of different and somewhat opposing influences. At any price, it earns revenue streams from (i) existing customers it captured earlier who decide against moving again, (ii) existing customers who, having searched other suppliers, decide to remain, (iii) switchers to it from the incumbent, and (iv) switchers from other entrants. The lower the price set, the higher the proportion of customers of types (ii) to (iv) will be achieved, but the lower the revenues per customer from each source. The parameters of this trade-off will vary with the proportion of customers of each type; for example if a large base of customers has been gained already, they are likely to weigh relatively heavily in the decision.

A model of the trade-off function facing a particular entrant was developed to examine this; the model is sketched in Appendix 4. We then engaged in some simulations, making a particular distributional assumption (the lognormal) and experimenting with some parameterization of the model. Two examples from the resulting distributions are illustrated in Figs 5 and 6 where the horizontal axis measures the range of possible prices between the marginal cost (set equal to 50) and the maximum consumer valuation (set equal to 100), the price the incumbent

\(^{21}\) These results are not reported here for brevity, but are available from the authors upon request.

\(^{22}\) We do not insist that firms play a mixed strategy, simply that the outcome of their moves appears like one.
will charge. The curves represent the entrants’ cumulative price distribution. The meaning of any one cumulative distribution function (cdf) is the distribution from which each entrant will pick its price in a mixed strategy equilibrium.

Figure 5 shows a range of distributions where the number of entrants is 6, whilst Fig. 6 is similar except that the number is 15. From these cdfs we can read off the median (as an estimate of the sample median) directly and get an impression of the likely empirical range of prices. The parameter which varies within the figures is the proportion of customers retained by the incumbent, \( \lambda \). Hence, at the start of the experiment, \( \lambda \) is one. By the end of our period, it is on average around 0.5. Comparing across the figures, if \( \lambda \) remained at one, the fall in the number of suppliers, \( N \), would have reduced median price, in line with our empirical finding (Table 4) on the effect of firm numbers on ML. But of course, all other things are not equal, and in the model as \( \lambda \) declines median price rises, holding \( N \) constant. Even allowing for falls in \( N \), the simulation indicates that median price will rise. The other finding is that the price range increases, in line with our finding regarding HL in the second period. It is also worth noting that the second period increase in HL empirically outweighs the negative trend in the earlier period. In sum, once we allow for significant reswitching, the empirical results we uncover are more easily understandable.

5. Conclusions

On one view, electricity supply is a homogeneous good market in which consumers quickly learn through their own or others’ experience how easy it is to switch

![Figure 5: Price cdf for several \( \lambda \) values. 6 entrant firms, lognormal (1,4) search cost distribution](image)

Note: \( \lambda \) is the initial market share of the incumbent firm. Marginal cost is 50 for all players, consumer valuation is always 100; the incumbent prices at 100.
suppliers in order to save money. As a result, companies aiming to capture new business would need to price competitively and companies wanting to retain business would need to ensure their offer did not move too far out of line with entrants’ offers. Hence as companies learnt more about their competitors’ moves, differences in the trend values of prices would tend to shrink. To some extent this has happened in the UK, but although a large proportion of consumers has switched there has until now been no comprehensive, substantive analysis of the prices consumers face. Our finding that there is a persistent incumbency advantage of almost 10% is significant but not completely surprising. The initially more surprising and significant finding is that it remains worthwhile for some non-incumbent suppliers to quote, and do business at, prices that are very significantly non-competitive, in the face of increased consumer experience and substantial switching.

Of course, during the first half of the sample period we are observing, price controls were operative on incumbent players. However removal of these controls has, if anything, led to the gains from switching supplier away from the incumbent to grow over time. Thus, whilst the market has not seen major anticompetitive moves by established players by any means, and whilst innovation in products has been observed, a fully competitive market in the LOOP sense has not emerged. Indeed competitive pressures seem somewhat damped. This conclusion is reinforced by the fact that retail electricity prices overall are somewhat insensitive to movements in wholesale prices over the period since a market has developed (OFGEM, 2003).

Why have prices not converged across suppliers? In a market where search is costly, at least in opportunity cost terms, we would not expect complete

Fig. 6 Price cdf for several $\lambda$ values. 15 entrant firms, lognormal (1,4) search cost distribution. Notes as for Fig. 5
convergence. Although the decline in supplier numbers would by itself suggest a lesser dispersion (albeit with a higher average price), as time passes those firms that previously were entrants have an increased incentive, when setting their prices, to consider not only the benefits from winning new customers but also the benefits of making money from those they have previously gained. The implication for consumers is, unfortunately, that a company which was once a ‘good buy’ and captured significant customer numbers may slip significantly in the rankings. As an illustration of what may be this phenomenon at work, British Gas gained a deserved reputation in the early years for being a good buy for electricity, and managed to obtain a large share of the electricity market. However, as a result of price rises, over the course of 2006 it became a markedly poor buy. Our results therefore suggest that consumers’ periodic renewed search for a supplier is likely to be worthwhile; the price correlations over time reported in Section 4.2 imply this should be as frequently as annually, in the current market.

Supplementary material

Supplementary material (the four-part Appendix) is available online at the OUP website.

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23 Admittedly, BG’s ranking improved significantly in 2007, outside our estimation period, as a result of significant customer numbers leaving the company.
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