**MARKET STRUCTURE AND ENTRY:
WHERE'S THE BEEF?**

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MARKET STRUCTURE AND ENTRY: WHERE'S THE BEEF?[1]

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ABSTRACT

We study the effects of market structure on entry using data from the UK fast food (counter-service burger) industry over the years 1991-1995. Over this period, the market can be characterized as a duopoly. We find that market structure matters greatly: for both firms, rival presence increases the probability of entry. We control for market specific time-invariant unobservables and their correlation with existing outlets of both firms through a variety of methods. Such unobservables generally play a minor role. For both firms, variable profits per customer are increasing in the number of own outlets, and decreasing in the number of rival outlets. Structural form estimations show that the positive effect of rival presence on the probability of entry is due to firm learning: rival presence increases the estimate of the size of the market. The firms are differently affected by demand variables and have different fixed costs of entry. These results strongly suggest the presence of product differentiation, firm learning and market power.

Keywords; duopoly, entry, fast food, learning.

JEL: L11, L13, L81, D83

1. INTRODUCTION

The development of chain stores provides a natural context in which to examine some central questions relating to multi-product firms. In this paper, of particular interest is the old and central, but empirically unanswered, question of the identity of the entrant(s). Are we more likely to see the incumbent firm opening a new store than to see the entry of a new firm? Also, does existing-firm presence, of whatever type, deter entry? Importantly, traditional (Industrial Organization) models of entry usually exclude the effects of learning. The standard model of entry predicts that, all other things equal, when a firm has the choice between two otherwise identical markets, in one of which it would be the monopolist, in the other of which it would face some competition, the firm will choose the monopoly market. However, if the potential entrant can learn sufficient about the profitability of a market by observing the existing rival's performance, is it possible that this strong prediction no longer holds true and may even be reversed?

We attempt to answer these questions by empirically analyzing the development of market structures in the UK counter service burger industry. Our paper has major novelties in four areas. First, it is a panel data study of entry. Second, by estimating firm-specific profit functions we allow for product differentiation. Third, the possibility of learning is introduced. Fourth, the structural estimates we present later are unusual in their error structure.

The ideal data set for analyzing these entry questions would consist of separate markets together with a clearly identified set of potentially active firms; where conduct largely does not vary over markets; where one observes entry in significant numbers; and where market characteristics (e.g. market size) vary over markets. The UK counter service burger market over the time period 1991-1995 has features that make it a particularly attractive case to study. Firstly, the market is well defined in terms of the goods the firms produce, and the products are reasonably close substitutes. Appropriately delimited, the markets can safely be assumed to be local and geographically separable, and our characterization of markets can be controlled for. Secondly, due to the centralized operations of these firms, conduct does not vary substantially over geographical markets. In particular, the locations and opening dates of outlets, their exact specifications, types of goods sold, and pricing policies are largely decided centrally and the outlets are reasonably homogeneous in type. Thirdly, the firms in question have aggressive expansion policies, as a result of which they open several outlets each year in a number of geographic, local markets and therefore provide us with a large number of observations. Fourthly, geographical and demographic data are available that relate to areas which are good proxies for local markets in fast food products.

Of no less importance, the industry can for practical purposes be characterized as a duopoly: the two dominant firms have a combined market share of over 60%. Moreover, the second and third largest firms had a legal agreement for most of the period of our study that prevented the latter from opening other than full service restaurants. This, in effect, foreclosed the third firm from the relevant market of burger sandwiches sold over the counter. Importantly, our data reveal that exit, i.e., closure of outlets, is a very rare occurrence for the duopolists. This, together with UK planning permits that effectively put a premium on retaining sites and an annual planning round for the firms, allows us to treat existing outlets differently from "new" entries, namely as predetermined variables embodying some sunk costs and thereby affecting the profitability of entry for both firms.[2] In other words, the industry is straightforward enough to enable a very detailed analysis of the players. Ours is the first study to do this in depth.

Recently, the interest in strategic aspects of firms' entry decisions has taken a turn from purely theoretical analyses (e.g. Dixit, 1979, 1980) towards empirical analyses of firms' actual entry or exit decisions (e.g. Bresnahan and Reiss (hereafter BR), 1989, 1990a,b, 1994; Berry, 1992; Reiss, 1996; Chevalier, 1995; and Scott Morton, 1999. There is also a marketing literature on entry: see e.g. Geisel et al., 1993). Many of these papers, however, either downplay the strategic issues relating to entry decisions, or else have used computationally involved methods that only allow the researcher to identify the "average" strategic effect. Common to several of these studies is that they treat the "entry" of *existing* firms (i.e., the continuation of operations) as identical to "true" entry of new firms to a given market, and that they do not consider the effects of learning. The former is equivalent to making the assumption that firms can in every period, without a change in costs, review their entry decision. Given sunk costs, we believe that particular assumption to be unwarranted, and we do not utilize it. In this paper, we do follow the lead of the cited papers to the extent that i) our theoretical point of departure is static (2- or 3-period) entry models, and ii) we take the unit of observation to be a geographical market (defined more accurately below).

In contrast to the markets studied in most of those papers (the exceptions are Chevalier, 1995 and Scott Morton, 1999), our market is a multi-plant duopoly, where the same two firms are (potentially at least) active in each of the markets. This last feature greatly simplifies the econometric estimation process, and allows us to use different estimation methods, and answer the key questions that have remained unanswered in previous empirical studies of entry behavior. In particular, we are able to derive explicit results on the strategic interaction of the firms for each firm separately, thereby allowing for both between and within firm-heterogeneity in both profits and entry costs, and to explore the effects of existing own and rival outlets on entry behavior. That is, we allow for and make an attempt at measuring both product differentiation, and learning. In addition, our data have a panel feature contrasting with the largely cross-sectional data employed thus far. Notice that we examine only one aspect of the entry decision-whether to enter an outlet into a particular area or not. This we consider separate from the decision of where in that market to place it, a question we will examine in subsequent research.

The remainder of the paper is organized as follows: in the next Section, we review the relevant theoretical literature and its predictions, and then develop an extension of the basic entry model that allows us to incorporate firm learning alongside more traditional factors. In Section 3, we describe and discuss the main features of the market and the data. In particular, we explain the definition of markets used, and provide evidence that supports our decision to treat the industry as a duopoly. Together, the economic models and the factual background enable us to develop two alternative econometric strategies in Section 4. Section 5 covers the results from a reduced form approach, whilst Section 6 details our structural form estimations. Finally, Section 7 offers some concluding comments.

2. THE MODELING APPROACH

2.1. Previous Research

Common to all empirical models of entry is the idea that new outlets (products), i, are attracted by the expectation of positive profits in the market, once fixed costs have been accounted for. Thus, entry occurs if:

(1) $E(\Pi_i) - F_i \geq 0.$

The early game theoretic literature on entry (Dixit, 1979, 1980, Milgrom and Roberts, 1982, Fudenberg and Tirole, 1984) concentrated on analyses of entry prevention and accommodation. Shaked and Sutton (1990) offer a useful presentation in terms of potentially observable variables. They look at the situation where an incumbent and a potential entrant each make a decision whether or not to open a new store (more generally, offer a new product). Their analysis highlights two opposing forces: expansion and competition effects. The expansion effect is measured by the fractional increase in the monopolist's profit, if it opens a new store. In their words, it 'measures the degree to which total demand is increased when a new product [store] is introduced' (p.47). The competition effect, on the other hand, measures the difference in industry profits between the new good being introduced by the incumbent and by the new entrant. As an example, if the goods are homogenous (and there is Bertrand competition), there is no expansion effect, but a very large competition effect. That is, the expectation of "tough" post-entry competition leads to less rival entry.

The standard theory predicts a negative relation between existence of an own store and entry, and the existence of a rival outlet and own entry (if there is any post entry competition), ceteris paribus, compared to entry into an otherwise identical market with no outlets of either firm.

Recently, it has been proposed (Caplin and Leahy, 1998) that other effects may exist. In particular, Caplin and Leahy advocate the view that firms may face considerable uncertainty as to the profitability of a given market. In such circumstances, the presence of a rival store may lead a firm rationally to update its beliefs about the profitability of entry. This "firm learning" model therefore predicts that the presence of a rival store has a positive effect on probability of own entry.

Similarly, one could envisage customer-based learning taking place. As we explain below, hamburger chains have a relatively short history in the UK. Thus it is possible that in a part of the market where no fast food outlets exist, the potential customers do not know the utility they would derive from consuming the good. If so, having one outlet in the market would mean that some consumers at least have found out their valuation of (say, McDonalds) hamburgers. Such consumer learning, or habit formation, would mean existing own presence increases the probability of own (additional) entry.

2.2. A Simple Model of Entry with Firm Learning

Consider the following model of entry. There are two firms, two identical periods (years in our data), and within each period there are two stages. In the first stage, the firms decide sequentially whether or not to enter a market; in the second, they compete e.g. in prices. In the next Section we explain why a leader-follower model of entry suits our data; from a theoretical viewpoint it serves the purpose of yielding a unique equilibrium in each period for all (cost) shock realizations, something which is problematic in this area. The nature of competition is common knowledge.

Consider the first period. We decompose a firm's demand into demand per customer, and the number of customers (following e.g. BR). Firms may earn different profits per customer and may attract different customers (i.e. their market sizes may differ); this is a reduced form way of introducing product differentiation between the players. Critically, we assume that firms do not initially know the size of their market, but have to form expectations, and act based upon them. The distribution of the true customer numbers for each firm (and therefore also its expectation) is common knowledge. The predictable part is the mean (expected) market size denoted $E[S_i]$, where the i (firm) subscript underlines that this may be firm-specific. We denote the random component of market size by μ, and assume that it is symmetrically distributed about its zero mean with a known distribution function $\varphi(\mu)$. The support of the population in a given market is $[\underline{S}, \overline{S}]$.

The other random element in the model concerns fixed costs of entry; we assume that the fixed cost of entry can be decomposed into a parametric component F>0 (for simplicity identical for both firms; this is not necessary) and a random shock. Both firms observe own and rival realizations of the cost shocks ε_{it} at the beginning of each period, before making entry decisions. These cost shocks have a normal c.d.f. $\Phi(0,1)$. In accordance with our data (see Section 3) which show that entry occurs in a relatively small fraction of cases, we assume that firms need a fairly 'good' (i.e. large) cost shock realization in order to find entry profitable.

For reasons of space, we do not develop a full characterization of the equilibrium here. For current purposes, it is sufficient to show how this simple framework may create two phenomena in equilibrium: first, the "follower" may enter before the "leader", and second, a firm may actually prefer entering a market where the rival is already present to entering an otherwise identical market where it would be a monopolist.

The most obvious means by which the follower enters where the leader chooses to stay away is when the leader gets a bad cost shock and therefore finds it unprofitable to enter, whereas the follower gets a good cost shock[3].

To allow for the second important feature we introduce learning. This necessitates there being a second period. Assume for the present, without loss of generality, that the existence of a rival outlet allows the firm to learn exactly what the market size is, i.e., observing rival presence in the first period allows the non-active firm to learn the value of μ.

Imagine first a market that neither firm entered in the first period. With the obvious changes resulting from the datum now being two instead of one, the second period situation is a replication of the first. Considering for simplicity only the problem of the follower after the leader has again decided *not* to enter (due to a (second) bad cost shock, for example), its expected profits can be written as

(2) $\Pi_F = E[S_F]\pi_F^M$.

The first right hand side term is the expected market size as predicted from market characteristics, and the second term represents follower's monopoly profits per customer. The follower will enter if and only if

(3) $E[S_F]\pi_F^M - F + \varepsilon_{F2} \geq 0$

With our standard assumption that ε_{Ft} is normally distributed with unit variance, the probability of entry is given by

(4) $\Pr ob(Entry_F) = \Phi(E[S_F]\pi_F^M - F)$.

To calculate the probability of entry when, alternatively, the leader did enter in period one, we must take into account that the follower now knows exactly the size of the market, but that this varies according to $\varphi(\mu)$. For a given realization of μ, revealed by the presence of the rival in the first period, the entry rule for the follower is enter if and only if

(5) $(E[S_F] + \mu)\pi_F^D - F + \varepsilon_{F2} \geq 0$

yielding the entry probability conditional on the realized market size as

(6) $\Pr ob(Entry_F \mid S_F + \mu) = \Phi((E[S_F] + \mu)\pi_F^D - F)$

The unconditional probability of entry, is therefore

(7) $\Pr ob(Entry_F) = \int_{\underline{S}}^{\bar{S}} \Phi((E[S_F] + \mu)\pi_F^D - F)\varphi(\mu)d\mu$.

Equation (7) is important since the data do not reveal μ to the econometrician, only the firms' response to learning it. Using the same logic, we could derive the entry probabilities for a leader who faces a market where the follower entered in the first period. It can then be shown that the following holds:

RESULT 1: If i) Φ(.) is (sufficiently) convex around $E[S_i]\pi_i^D - F$, and ii) duopoly profits are a large enough positive fraction of monopoly profits, the entry probability into a market where the rival has an outlet may be higher than the entry probability into an observationally identical market with no outlets of either firm.

PROOF: Assume first that monopoly and duopoly profits are identical. The result then holds strictly, from (4) and (7), due to the (assumed) convexity of Φ(.) around $E[S_i]\pi_i^D - F$. By continuity, it holds for the case when duopoly profits are strictly less than monopoly profits. QED.

To justify our maintained assumption that Φ(.) is convex in the relevant region, note that in our data, the (unconditional) probability of entry is less than 10% for both firms. The following simplified case illustrates the result: let the market size be either S-$\bar{\mu}$, or S+$\bar{\mu}$ (where $\bar{\mu}$ > 0 is some known constant), both with equal probability. Also, assume for the moment that monopoly and duopoly profits are identical. Consider then Figure 1, where we have depicted a situation where Φ(.) is convex around $E[S_i]\pi_i^M - F$. The entry probability into a market with no rival outlets is given by $\Phi(E[S_i]\pi_i^M - F)$; the entry probability into a market with a rival firm already established is $\Phi((S - \mu)\pi_i^M - F)$

with probability ½, and $\Phi((S+\mu)\pi_i^M - F)$ also with probability ½. From the vantage point of the econometrician who does not observe μ, the probability of entry into a market where the rival already has an outlet is the linear combination of these. Since Φ(.) is convex, the linear combination is strictly larger than the mean value of the function (the entry probability $\Phi((S-\mu)\pi_i^M - F)$ is smaller than $\Phi(E[S_i]\pi_i^M - F)$ by amount equal to area "A" in Figure 1; the entry probability $\Phi((S+\mu)\pi_i^M - F)$ is larger than $\Phi(E[S_i]\pi_i^M - F)$ by the area "A+B"). Because the entry probability is strictly larger into a market with rival presence yielding equivalent profits, by a continuation argument duopoly profits can be strictly less than monopoly profits, and still there is a larger entry probability into a market with rival presence, than into an otherwise identical market with no rival presence.

Result 1 extends the logic of Figure 1 to allow for a continuous distribution, but the argument remains the same. Now equal weight is given to each market size realization that deviates by the same (but oppositely signed) amount from the expected market size; there is an infinity of values that the deviation can take instead of one. Note that we assume only two things of μ: firstly, that it is symmetrically distributed around its mean; the distribution need not be unimodal, for example. Secondly, that Φ(.) is strictly convex round the point determined by the entry threshold without learning. The latter could be relaxed to some extent[4]. It is important to recognize the effect of post entry competition on how rival presence affects entry probabilities. If firms compete in homogenous goods in Bertrand fashion and no capacity constraints, no amount of learning leads to an increased entry probability.

Finally, note that so far we have restricted the analysis to the case where firms perfectly learn the market size from observing the rival outlet's performance. More generally, and especially regarding our data, the assumption that a firm gets only an imperfect signal from observing a rival outlet leads to a more realistic empirical prediction. Such a structure leaves room for the firm to learn from additional rival outlets; this we will allow for in the empirical analysis.

3. THE DEVELOPMENT OF THE UK FAST-FOOD MARKET, AND THE DATA

3.1. The Market Definition

The market we are interested in is an essentially local counter-service market. Counter service is a significantly different product from table service, in view of the time element, for example. We also distinguish this everyday market from the *transit* market, a relatively recent phenomenon in which Burger King (particularly) operates from motorway service areas, station forecourts (having taken over another company's operations there) and airports. We do not seek to examine the transit market, because substantially different factors such as passenger flows are most likely involved. Note that in this respect the UK fast food market is very different from the US market, where the majority of fast food outlets are transit outlets. By contrast with the transit market, the local market (*pace* BR) is influenced by population, incomes, etc. Thus our ideal unit of observation is the local market, also the observation unit of BR and Kalnins and Lafontaine (1997), for example. But in BR's case, the authors have a situation probably not available anywhere in Europe, genuinely isolated markets largely in the Midwest United States. By contrast, our markets are inevitably bordering other markets, and we therefore control for this.

In examining local markets, we take an essentially pragmatic approach. People in Britain do not travel far to satisfy their fast food needs. We choose the unit of observation to be local authority districts. There are approximately 500 such districts in Great Britain. Our presumption is that people (save those near a boundary) seldom travel outside their district in search of fast food. Possibly, they will not be willing even to travel the full extent of the district. Prima facie evidence for this is that some densely populated districts have several branches of the same burger chain. But we wish to observe entry behavior. Defining the unit of observation very narrowly will mean new entry is a very unlikely event, and so lead to difficulties in estimation. Local authority districts provide a compromise for which demographic and other data are readily available. They are also (normally) centered on a particular town.

3.2. Why the Market is a Duopoly

Our decision to treat the industry as a duopoly rests essentially on three facts: first, there is only one other hamburger chain (Wimpy) that is large enough to be considered a strategic player in the market. Secondly, due to the service format that Wimpy has adopted, it can be considered to be producing a different good. Thirdly, for historic reasons outlined below, Wimpy was specifically excluded from the relevant market for most of our chosen observation period, and thereafter chose to stay out.

Traditionally (and as recently as 25 years ago), the UK fast food market was dominated by small local suppliers who did not produce branded products. This has now changed rapidly as a result of entry by the largely US-based burger, chicken and pizza chains. The burger market more particularly is dominated by three players: McDonalds (McD), Burger King (BK), and Wimpy. They have sales shares estimated (MAP, 1994) at 40%, 20% and 18% of the market, respectively, in 1994. These three players are estimated in the same publication to have 45% of the entire “big name” fast food outlets in the UK. Burger operators who have had success in other countries, including Wendy’s and Quick Burger, have failed to establish a successful foothold in the UK. There are some smaller chains, of limited impact, one of the largest being Starburger (with approximately 60 outlets compared with over 400 for BK and over 600 for McD in 1995), and some strictly local outlets, but barriers to the entry of new large chains are likely to be significant.

[TABLE I HERE]

The history of our industry is set out in Table I. Several important features emerge. McD appears to be a straightforward story of continuous success as the leading player, with growth arising entirely organically, whereas the Wimpy/ BK relationship is much more complex. In 1988, Grand Metropolitan acquired Pillsbury and with it BK. Then in 1989, it purchased UB restaurants, the owner of Wimpy, and so owned both chains. In 1990, Wimpy International was formed by a management buyout from Grand Met. However, Grand Met. insisted on a three year agreement running to June 1993 which prevented Wimpy opening up any counter-service or drive-through outlets (MAP, 1994). Consequently, Wimpy suffered from a "60's" image with its forced reliance on counter service, and by being disallowed from competing in the major growth markets. However its ambitions seem modest in any case. As an illustration, in 1993, its advertising expenditure was estimated at less than £0.5m, as against £27.3m for McD and £6.7m for BK. The year 1994 (the first year after the agreement between Wimpy and Grand Met had expired), has McD spending £31.3m, BK spending £8.2m and Wimpy £0.6m, and later years show a similar picture, with Wimpy's expenditure averaging around 1/10 of BK's over the 1990s (data from MEAL, various years). All its 240 outlets were table service (and therefore outside our defined market) in 1994 and by mid 1996, it had only grown to 272 outlets, largely by developing at service stations (Financial Times archive). Thus there is a considerable contrast with BK, which after a shaky start, grew rapidly and continuously once consolidation had taken place in the hands of Grand Met in 1990.

We study the development in terms of store openings of the industry from 1991 to 1995. The choice of dates is deliberate. BK's consolidation, as a result of rebadging of former Wimpy outlets, was complete late in 1990, and growth since then has largely been organic (and purely transit-oriented branches which are not, we exclude from consideration). Wimpy was prevented from, or at the end of the period chose not to, compete directly in the prime market for McD and BK, namely counter service. This means - using the above market share figures and subtracting Wimpy's share from the total - that the two firms we examine hold a combined share of 75% in the relevant market. Thus, since counter service burgers is the market under study, there are only two strategic players over our period, BK and McD.[5] Based on its earlier start and larger share, plus discussions with market participants, we think it is justifiable to consider McD the leader in the industry.

Naturally, both firms take into account any local competition in the market in making entry decisions. In our empirical specification, we allow for such unobserved market-specific effects: we will merely assume that they do not affect entry decisions in the same way as the actions of the other strategic player. We have not gone beyond 1995 in part for reasons of data availability and in part because the CJD ("mad cow") beef scare is likely to have affected all players' plans and consumption in 1996. Also, Wimpy might by then be argued to be (potentially at least) a strategic player in the local drive-through market.

3.3. Data

Briefly, the basic data on store locations and openings comes, in McDonalds' case, entirely from the company itself. These data are very high quality and very useful for other reasons. For example they establish that exit is a very unusual phenomenon; less than 1% of all the stores ever opened in the UK have closed. In the case of Burger King, the data come from more of a variety of sources, although we do have a complete listing of stores in 1995. Again, exit is unusual, though more common than for McD.

The basic data on the demographic and other characteristics of local authority districts come from Regional Trends. These two data sources (on outlets and on demographics) are matched using a Midas "Postzon" package based on UK postcodes. A third source (the "AA"'s "A to B") gives distances between districts. More detail on construction of each of the variables, including definitions, sources and problems, is given in the Data Appendix which is available on request.

The estimation sample consists of five annual observations each for 452[6] districts-we exclude Northern Ireland, all small islands apart from the Isle of Wight, and three London boroughs (see footnote 5). For each such district market, we observe the geographical area and population, the proportion of under-16s and pensioners, the council tax rate, average wage rate, and unemployment rate. We also observe the market structure at the beginning of the period, and whether or not entry by one or the other firm occurred during the period (calendar year). In addition, we know the distance from the market to the headquarters of both firms, and the number of outlets of both firms in the neighboring markets. The population data are annual; certain of the other demographic variables are not observed every year for every market. In such a case, we substitute the last observed figure, and include dummies for these observations. In particular, the YOUTH and PENSION variables are not available for 1995 in 60 of our markets. For these markets, we use the regional average, and add a dummy. Wage is observed at the regional level, not the district level, and only for 1991 and 1992. We used the 1992 wage figures for the later years, and control for changes in wage levels (together with other omitted time-varying effects) in subsequent years by including time dummies in all specifications. The descriptive statistics of the sample are given in Table II.

[TABLE II HERE]

As the descriptive statistics reveal, the markets are very heterogeneous. Geographically they vary between 15 and 6497 square kilometers, whereas the population varies between 11,000 and over a million. The furthest market is 674 miles from McDonalds headquarters. The other demographics, and the economics of the markets also vary substantially, for example pensioners make up as much as one third and as little as 12% of specific markets. One would therefore expect market structures, and observed entry patterns also to vary, and this is what we see. Predictably, the changes over time are relatively modest for most variables e.g., population growth is on average less than 500 p.a.

[TABLE III HERE]

In Table III we give some statistics relating to the number of outlets, and the number of entries. As can be seen, McD is clearly larger than BK. Our sample includes a clearly larger proportion of McD than BK outlets: the main explanation for this is are BK's smaller size and its relatively large number of transit outlets (these constitute 25% of BK's, but only 7% of McD's stock). Although BK has grown faster in relative terms during our sample period, McD has grown faster in absolute terms. Notice also the large difference in the proportion of franchised outlets.

[FIGURE 2 HERE]

Let us take a first look at the market structure and entry data. In Figure 2 we detail the proportions in which different market structures are observed, and display the firms' entry behavior conditional on market structure. A code (M,B) refers to a market structure where McD has M, and BK B, outlets at the beginning of the period. Some market structures (e.g., (0,3)) are never observed in the data, and others appear very infrequently. We have therefore included as final categories market structures with firm i having 3 or more outlets, and firm j either 0 outlets (labeled (I,0) and (0,I)), or fewer outlets than firm i ((I,<I) and (<I,I)). The largest number of McD outlets in a market (as of beginning of period) observed is 14, that of BK 7.

Two interesting observations can be made. First, that entry into new markets is observed with a lower probability than entry into markets where at least one of the two firms is already present. Second, that existing rival outlets seem to increase the probability of entry. For example, the sample proportion of entry for market structures with one BK and no McD outlets is 21% for McD and less than 7.1% for BK; the corresponding numbers when the market structure is one McD outlet and no BK outlets are 7.2% and 12.8%. Likewise, the entry probabilities in markets where the rival has two, and the firm itself no outlets are far higher than the entry probabilities in the markets where the structure is reversed. Generally, it seems that entry appears rather unconstrained by high numbers of (rival or own) outlets.

In our econometric specification, our dependent variable will be 'entry by firm i into market j in period t'. We will thus not differentiate between opening of one, and opening of multiple outlets within a year. This choice is driven partly by a search for simplicity, partly by the data. Over 90% of observations with positive entry are of single outlet entry.[7] Thus we treat the entry occurrence as being a single entry, and observe 183 entries thus defined for McD, 157 for BK. For BK, there are a few outlets for which we did not obtain the entry date (14 occurrences). In these cases, we treat the outlet as if it was opened prior to our observation period, and attach a dummy to it. Omitting the relevant districts from the estimation sample made no difference to the results. There are only 31 cases of both firms opening a new outlet in a given market in the same year. Most (24) of these are cases where both firms open one outlet; there is one case where BK opens three and McD one, and one case where both open two. The remaining 5 cases are where one or the other firm opens two outlets, and the rival opens one outlet. Though this is only a small proportion of all observations, simultaneous entry observations constitute 10.0% of all those observations with positive entry.

We have also cross-tabulated the market structure *at the end* of 1995 with population (as in BR).[8] We found that the smallest market population for which there exists a McD outlet is 41,300, for BK the figure stands at 53,900. These cross-tabulations provide the information that not all the districts in our sample appear to be viable markets. If some of our markets were truly 'impossible', including them in the data would bias our results.[9] Using the McD population threshold as a filter would lead us to exclude 137 district observations, whereas using BK's threshold would exclude 262 (less than or at most 10% of all observations, but roughly a quarter of new market (0,0) structure observations). We therefore explored the effects of excluding some markets from the sample on grounds of small size.

4. ECONOMETRIC MODELS AND METHODS

4.1. A Reduced Form Approach

As a first (econometric) pass at the data we estimate the following reduced form entry function (as suggested by Reiss, 1996; Berry, 1992):

(8) $$\Pi_{ijt} = X'_{ijt}\,\beta_i + g(n_{jt}, m_{jt}, \theta_i) + \upsilon_{ijt}$$

Subscript i denotes firm ($i \in \{M, B\}$, where M stands for McD and B for BK), j market, and t the time period; the vector X_{ijt} includes market and (possibly) firm specific variables; and g(.) is a function of existing own (n_{jt}) and rival (m_{jt}) outlets in market j (see also Mazzeo, 1999). We explore different ways of measuring market structure, two of which are: i) a count variable for the number of outlets of firm i, i = M, B; and ii) a vector that consists of indicator variables that take the value unity if the observed market structure is (n_{jt}, m_{jt}). In addition to the usual problems with reduced form, an additional problem is that (8) does not allow a rich way to control for the opportunity cost of not entering. In particular, it seems reasonable to assume that the profits from not having any outlets in a market are zero; but that where $n_{jt}>0$, the opportunity cost is non-zero.[10] In this specification, the difference is captured solely by the market structure indicators. The error term ν_{ijt} captures the effects of events not observed by the econometrician. Econometrically we explore different specifications of ν_{ijt}, and in particular, the possibility that it contains market (and firm) -specific, time-invariant components. It is a maintained hypothesis throughout that decisions are taken in every region in every time period.

4.2. A Structural Approach for Multi-outlet Firms

Consider now the following alternative. Our theoretical model borrows its structure from standard two-stage entry games, where in the first stage, firms decide whether or not to enter, and in the second, compete in prices or quantities. Utilizing panel data means that we view our firms playing this game every year (= period), and the question is rephrased as whether or not to open a new outlet.[11] Having a static model means we assume that firms do not take into account the effects that this period's decisions have on future periods' decisions. We will however to some extent control for this by conditioning entry decisions on existing market structure, i.e., past entry decisions. The form of second stage competition is common knowledge among the potential entrants.

To operationalize the theoretical model of Section 2.1, we assume, in line with BR, that the (reduced form) profit function of the firm net of entry costs, resulting from competition in the second stage, is of the form

(9) $\Pi_{ijt} = S_{ijt}(.)V_{ijt}(.)-F_{ijt}(.)+e_{ijt}$

where S(.) is market size, V(.) gives the variable profits per potential customer, F(.) denotes the fixed entry costs (possibly unobserved by the econometrician), and e_{ijt} is the period and firm specific (i.i.d. normally distributed) shock to these costs. The functions S(.), V(.) and F(.) contain market and firm specific, possibly time-varying variables, and the number of own and rival outlets may enter each of the functions.[12]

Consider first the problem of a single (non-strategic) firm deciding whether or not to enter a market where it has no outlets. Being non-strategic means that the firm ignores the rival's decisions, and assumes that the number of rival stores stays constant, i.e., $m_{jt}=m_{jt-1}$. Clearly, the firm will then enter if and only if

(10) $\Pi_{ijt}(1) = S_{ijt}(.,m_{jt},1)V_{ijt}(.,m_{jt},1)-F_{ijt}(.,1)+ e_{ijt} >0$

Here we have set $n_{jt}=1$, and normalized the profits from having no outlets to zero. It is straightforward to generalize (10) and show that (a non-strategic) firm's decision rule for opening the n^{th} store into market j in period t is given by "enter if and only if"

(11) $\Pi_{ijt}(n_{jt})= S_{ijt}(.,m_{jt}, n_{jt})V_{ijt}(.,m_{jt}, n_{jt})-S_{ijt}(.,m_{jt}, n_{jt}-1)V_{ijt}(.,m_{jt}, n_{jt}-1)-F_{ijt}(.,n_{jt})+ e_{ijt} >0$

In (11) we have maintained the assumption that a firm contemplates opening one new outlet against opening none, empirically the most common decision. The firm takes into account the profit difference between operating n stores and the foregone profits of operating the old number of stores (n-1), and the fixed costs of opening the n^{th} store. It is straightforward to generalize (11) to allow for any number of (new) outlets.

Modeling strategic entry decisions is more problematic, as shown in the seminal contributions of BR (e.g. BR, 1991). In this case, the equilibrium response of the rival matters. As BR show, one cannot econometrically model a simultaneous move entry game as a system of simultaneous equations, because the equilibrium configurations are not uniquely determined.[13] However, if firms make their entry decisions sequentially as we assume, this problem does not surface. Under such an assumption, the follower takes as given the leader's decision, hence the value it assigns to m_{jt} is the actual number of rival outlets *at the end* of period t. The leader takes the follower's optimal response into account when making its entry decision, i.e., $m_{jt}=m(n_{jt})$ for the leader.

4.3. Modeling Firm Learning and Market Unobservables

Our theoretical model assumes that firms do not know the size of the markets ex ante, but act either on expectations, or after having learned (more about) the market size by observing the rival in the previous period. This implies that if firm learning effects are present, a firm's estimate of market size at the beginning of a period, on which it bases its entry decision, is affected by the number of existing rival outlets. We model this by specifying that expected market size is a function of the number of rival outlets in market j at the beginning of period t.

It is entirely possible that there are important market specific determinants of entry that we do not observe; panel data allows us to control for those using random effects, for example. However there is the important decision of where to place the market specific unobservable in the profit function, i.e., what interpretation to give to it. The standard solution would be to add it linearly. This would imply that unobserved heterogeneity would be due to unobserved between-market differences in fixed costs of entry. Although these may well exist, a more plausible assumption is that our measure of market size does not capture all permanent differences between markets. Under this specification

(12) $S_{ijt}(.) = S_{jt}'\beta_i + s(m_{ijt},\theta_{Si}) + \rho_i\, \eta_j.$

In (12), S_{jt} are exogenous market characteristics that affect market size, s(.) is a function of the number of existing rival outlets, ρ_i determines the variance share of the random effect, η_j is the market-specific time-invariant error term, and β_i, θ_{Si} and ρ_i are firm specific (vectors of) parameters to be estimated. In standard fashion, we assume that η_j is i.i.d. normally distributed with zero mean, that $cov(\eta_j,\varepsilon_{ijt})=0$, and that $\sigma_\varepsilon^2 \equiv 1$. Theory suggests that learning cannot lower the expected size of the market.[14]

4.4. Modeling Variable Profits

The model employed by BR states that the profits of the firm are given by the product of market size and variable profits. To provide as direct a comparison as possible to their (and e.g. Berry's) results, we estimate models where

(13) $V_{ijt}(.) = V_{jt}'\gamma_i + v(n_{ijt},m_{ijt},\theta_{Vi}).$

V_{jt} is a vector of market specific variables, v(.) a function of own and rival outlets, and γ_i and θ_{Vi} are firm specific parameter vectors to be estimated.

4.5. Estimation of the Random Effects Models, and the Leader Equation

The introduction of random effects (equi-correlated errors) presents two difficulties: first, as the error component is placed in S(.), it is multiplied by V(.), rendering standard estimation methods for panel data discrete choice models unusable; second, it emphasizes the need to deal with the problem of spurious state-dependence (Heckman, 1981). A third problem is how to deal with the endogeneity of follower entry decisions when estimating the leader's choice.

Our solution to the first problem is to use a simulated maximum likelihood (MSL) estimator (see e.g. Hajivassiliou, 1997, for a recent exposition[15]). We opted for MSL instead of simulated method of moments (MSM) or some other simulation estimator for reasons explained by Hajivassiliou (1997) and endorsed by Hyslop (1999). The distribution of our dependent variable is relatively skewed (see Section 3), and MSL has proven more robust than other simulation-based estimation methods in such circumstances. Our limited experiments with MSM confirmed this to be the case with our data. Given that the time-invariant component of the error term is in S(.), leading to a model with random coefficients, we operationalize the simulation estimator by taking R (R = the number of simulation draws) times NT (the number of observations) independent draws of pseudo random numbers for the error terms η_j and (if necessary)[16] ε_{ijt} (i.e. the time-invariant, market specific, and the i.i.d. component of the error vector) from a standard normal distribution. We employ a decomposition simulation estimator (see e.g. Stern, 1997), setting R=40, and use antithetics. Antithetics is a powerful variance reduction method (e.g. Stern, 1997) that greatly reduces the simulation error. We performed a small scale Monte Carlo simulation study (described in the Simulation Appendix which is available upon request) to ascertain that our estimator performs well with the assumed error structure, and this turned out to be the case. In particular, the simulation exercise revealed that the correct assumption as to where the random effect enters the specification is crucial for the performance of the estimator. For this reason, we also tested the robustness of our results for the standard assumption of the random effect, namely that it is additively separable (and therefore, in our specification, part of the fixed costs of entry).[17] The simulation study also revealed that not allowing for random effects when they are present leads to badly biased point estimates.

A solution to the second problem is in many ways crucial to the interpretation of our results, especially if there turn out to be unobserved market specific factors that affect entry behavior. If these unobservables are positively correlated between firms, an estimated positive effect of rival presence on the probability of entry could be spurious, reflecting the unobservables' effect on (rival) entry. It is therefore likely that the number of existing outlets, both own and rival, are correlated with the unobservables, were these to exist. Note that our problem is not quite the standard one of Heckman (1981). The difference is that we have to be concerned not only with past decisions of the firm in question being affected by unobservables, but also its rival's past decisions having been affected by them. We control for this in the estimations of the structural model by projecting the market specific time-invariant unobservables onto both own and rival existing outlets. In the reduced form estimations we do not control for this save that in the linear probability model we use the Within group ("fixed effects") estimator which is robust to correlation between the time-invariant market specific indicators and the explanatory variables.

Regarding the third problem, the solution is i) to identify the system off the functional form and ii) to simulate follower (BK) response to leader (McD) entry. There are no obvious instruments available since any market characteristics that are likely to affect firm i's entry will most likely affect firm j's entry, too. This holds in particular for stocks of both own and rival outlets and locational variables. To illustrate ii), assume for a moment that there is no unobserved heterogeneity and thus we can use normal probit ML to estimate BK entry. We can then use the estimated BK coefficient vector to calculate the follower's (BK's) expected profit from entering market j in period t when the leader (McD) has entered in that period, and when it has not. Call these estimated profits $\hat{\Pi}^{BK}_{McD} = \hat{\Pi}^{BK}(.,M_{jt}+1)$ and $\hat{\Pi}^{BK}_{noMcD} = \hat{\Pi}^{BK}(.,M_{jt})$, respectively. In the former, it is assumed that McD's stock of outlets is one greater than it was at the beginning of the period, whereas in the latter it is equal to that at the beginning of the period. Note that we assume that a new McD outlet does not influence BK's estimate of market size (S(.)), but only its variable profits (V(.)). We then draw R (times NT) pseudo random numbers $\hat{\varepsilon}_{Bjt}$ from a standard normal, and create simulated BK entry decisions based on $1(\hat{\Pi}^{BK}_{McD,jt} + \hat{\varepsilon}_{Bjt} \geq 0)$ and $1(\hat{\Pi}^{BK}_{noMcD,jt} + \hat{\varepsilon}_{Bjt} \geq 0)$, where 1(.) is an indicator function taking the value one if the statement in parenthesis is true, and the value zero otherwise. These are then added to the existing BK outlets and used in the McD likelihood function in place of actual BK outlet figures.

5. REDUCED FORM RESULTS

In this Section, we first present reduced form results, and then discuss different robustness tests based upon them. We report probit and linear probability model (LPM) results for both firms. Both are estimated using controls for unobserved heterogeneity. We employ a random effects estimator for probit,[18] and a Within estimator for LPM. We include the following variables into the X_{ijt} vector of equation (8): POPulation (which in all estimations population is measured in 100 000's), AREA (thousands of sq. km.), proportion of under 16-year olds (YOUTH) and the proportion of PENSIONers, the UnEmployment rate (all three measured as a fraction), Council TAX (measured in £000; our proxy for real estate costs), average WAGE (measured in £100 000 p.a.; to control for wage costs/average income) dummies for markets within LONDON and bordering with one or more London markets (LONNEAR). In addition, we include a full set of time dummies, a dummy for those markets with missing BK opening dates, and a dummy for missing youth/pension or council tax data.

The market structure function g(.) makes use of the market structure dummies used in constructing Figure 1, where variable name MiBj indicates a market structure with i McD outlets and j BK outlets at the beginning of the period. We should point out that the vectors of market structure dummies employed for the two firms are different, because in a discrete choice model one cannot use as a regressor a dummy variable if for any of the values it takes, there is no variation in the dependent variable (see e.g. Greene, 1995, pp. 416). Thus, for example, we excluded the dummies M0B2 and M1B2 from the BK estimation as there was no BK entry into such markets during our observation period. The omitted market structure is a market with no existing outlets of either firm. Finally, we include as control variables the number of own and rival outlets in neighboring markets (the number of outlets of firm i at the beginning of year t in neighboring markets to market j, labeled OWNNB and RIVALNB respectively).

5.1. Results

We first look at the market characteristics (probit results) in Table IV. For BK, we find that AREA carries an insignificant coefficient, POPulation a significant positive coefficient, and POPAR and PENSION negative and significant (at 6% level) coefficients. The considerable importance of population for BK is similar to the results reported by BR in their various papers. We find that none of the market characteristics affects McD's entry decisions. Unemployment (UE) and the level of the council tax (CTAX) do not seem to matter to either firm. We also find that for neither firm is there a London effect in the data as LONDON obtains an insignificant coefficient. Our controls for market definition obtain significant coefficients for BK, and insignificant ones for McD. The LPM estimates are in line with the probit findings apart from POPulation becoming significant for McD.

[TABLE IV HERE]

The variables of most interest however are the market structure variables. Looking first at BK, we find that all the market structure variables bar M2B1 characterizing structures where McD has more outlets than BK carry positive and significant coefficients. For McD we observe a clear pattern in that almost all market structure dummies obtain a positive and significant coefficient. BK is thus – ceteris paribus - consistently more likely to enter markets where McD is larger than itself, than a market with no outlets of either firm. McD is more likely to enter markets with either firm's outlets, than comparable new markets. The LPM results are again in line with those of the probit estimates, although generally with weaker levels of significance.

Traditional IO theories (e.g. Shaked and Sutton, 1990) cannot explain the positive effect of rival presence on own entry; learning models can. Since own presence does not have a positive effect on entry for BK, consumer learning or habit formation is unlikely to explain the results. With habit formation, one would expect own presence to have a positive effect, as (supposedly) habit formation would lead not only to increased hamburger consumption in general, but to increased consumption of the firm's own hamburgers (rather than the rivals) in particular. The most plausible explanation of the pattern of results is therefore firm learning. The results further suggest that learning effects are strong enough to dominate any negative effects that competition between firms may have on entry decisions. However, the fact that almost all market structure dummies carry positive and significant coefficients in the McD estimation, and that population (in the probit estimation) is not significant suggest that the market structure dummies are picking up “too many” effects. This is despite us including controls for market specific unobservables.

5.2. Robustness Checks

The first robustness issue relates to unobservables. Because we have panel data, we are in a position to control for these, by including market specific error terms (the so-called equi-correlated, or random effects, model; or more general GMM estimators (see Breitung and Lechner, 1998)) in the probit estimation, or market specific controls (Within estimator) in the LPM. Of these, the fixed effects (Within) estimator is robust to correlation between the fixed effects and explanatory variables. The results presented in Table IV include these controls which unfortunately did not work very well. For McD, the estimated variance share was zero in the probit estimations, and that for BK was very low and highly insignificant. In the LPM estimations, the fixed effects were jointly insignificant for both firms. To explore this issue further, we estimated restricted models to see at what level the controls for unobservables become significant. It transpired that as long as we had POP (and even when having only POP) as an explanatory variable, the random effects (fixed effects in LPM) were insignificant and very small. The McD results in particular suggest that a problem with unobservables could exist despite these controls.

One possible objection is that our chosen length and timing of the empirical equivalent of the game theoretic model's entry stage – a calendar year – is ad hoc. There are however both qualitative and quantitative reasons why a calendar year is a natural choice. For one thing, both firms are quoted companies, and necessarily report their activities (including the openings of new outlets) in published annual reports. They both also announce annual plans of new outlets to be opened. More quantitatively, we have looked at the within-calendar year timing of McD's outlet openings which we have for a longer period. Using data from 1980 onwards (prior to 1980 the number of outlets opened was significantly smaller) it is clear that most outlets are opened towards the end of a calendar year. On average, over 30% of all outlets are opened in the month of December alone; 56% are opened in the 4th quarter; and only 5.4% in the 1st quarter.[19] Thus there is significant evidence that the calendar year is the planning period for these firms.

Then there is the issue of the sample for estimation. As mentioned in Section 3, a substantial proportion of markets has no outlets of either firm. Our estimations indicate that the most important variable (measured in terms of increasing the number of correctly predicted outcomes) is the population in a given market. Cross-tabulations reported above show that a selection rule 'exclude all observations with population below the lowest population that has attracted an outlet by firm i', does not reduce the sample greatly, but does lead to a significant decrease in the proportion of markets with no outlets. We find, however, that our estimation results are not sensitive to excluding 'impossible' markets. We also experimented with leaving out London, as the market structures there are different (having more outlets of both firms) than in the rest of the country. Again, our qualitative results are unaffected, with one exception: POP became significant in the McD estimation.

Finally, we experimented with including growth rates of market characteristics (to control for changes in expected size and characteristics of the market), and the lagged entry decision of the rival (to control for the possibility that firms react with a lag on rival entry) into the estimating equation. Whilst the results were otherwise unaffected, none of the new variables was significant. Our results turned out to be robust to the various functional forms we tried. We also estimated the model excluding the 1995 data to control for the expiry of the contract between Grand Met (BK) and Wimpy. The results for that sub-sample did not differ significantly from those reported. In sum, our results are robust to a variety of specification changes.

6. STRUCTURAL MODEL RESULTS

In the structural model estimations we assume, based on the discussion in Section 3, that McD is the leader and BK the follower. This assumption guarantees the uniqueness of the (sub-game perfect) Nash equilibrium, and endogenizes the market structure variables for McD.

6.1. Empirical Specification

We assume that S(.), V(.) and F(.) are linear functions. We employ the following specifications

(14) $S_{ijt}(.)=POP_{jt}+\beta_{i1}YOUTH_{jt}+\beta_{i2}PENSION_{jt}+\theta_{iS1}OWN_{jt}+\theta_{iS2}RIVAL_{jt}$

$+\theta_{iS3}OWNNB_{jt}+\theta_{iS4}RIVALNB_{jt}$,

which in some estimations we amend by adding the market specific time-invariant error term $\rho_i\eta_j$ (see Section 4),

(15) $V_{ijt}(.)=\gamma_{i1}AREA_{jt}+\gamma_{i2}WAGE_{jt}+\theta_{iV1}OWN_{jt}+\theta_{iV2}RIVAL_{jt}+\theta_{iV3}OWN_{jt}*RIVAL_{jt}$

$+\theta_{iV4}OWNNB_{jt}+\theta_{iV5}RIVALNB_{jt}$

and

(16) $F_{ijt}(.)=\delta_{i0}+\boldsymbol{\delta_{it}}'\mathbf{t}+\varepsilon_{ijt}$,

where OWN and RIVAL are the numbers of existing outlets in the district and $\mathbf{t}$ is a vector of indicator variables for years 1992,…, 1995. As stated earlier, we assume for identification that the error term ε_{ijt} is distributed $\Phi(0,1)$.

Population is likely the leading determinant of market size, but because different age groups may display different tastes for eating hamburgers, we add age group controls into S(.). We include own and rival outlets in neighboring markets in S(.) since if tastes are correlated among neighboring markets, firms may use information they learn in adjacent markets to update their predictions of market size in a particular market. The coefficient of POPulation in S(.) is normalized to one following BR. The coefficients of the S(.) variables can then be interpreted as increases or decreases in expected market size, measured in population equivalents.

Incorporating the set of neighborhood variables into V(.) has two motivations. First, the number of own outlets in adjacent markets allows a control for possible economies of scale in distribution. The firms have some regional facilities that may serve several of our markets. If these operations are characterized by economies of scale, we would expect θ_{iV4} to obtain a positive value. Insofar as the rival's operations share this characteristic, the number of rival outlets in neighboring markets affects rival's marginal costs in market j, and therefore its market position in that market. If so, we would expect θ_{iV5} to carry a negative sign. We include the geographical area, and average wages in the variable profits function. The former affects average travel costs and thereby decreases the utility consumers derive from patronizing an outlet. The latter on the one hand shifts out the budget constraint (indicating a positive relationship), and on the other, may lead to higher wage costs (indicating a negative relationship). Including own and rival outlets into V(.) needs no explanation.

Before turning to the results, we point out that in all our estimations the coefficient of own outlets in S(.) was either insignificant, or carried the wrong (negative) sign. We interpreted this as a problem of identification (relative to V(.)), and therefore, excluded the variable OWN_{jt} from S(.) in all the structural form estimations.

6.2. Follower (BK) Results

The results for BK are reported in Table V. We have estimated the model for both firms under the assumption of a standard probit error structure, and assuming an equi-correlated error term where the market-specific time-invariant error term is 1) in the market size function S(.), and 2) part of the fixed costs of entry. The first set are estimated using ML for BK (the follower) and MSL for McD (the leader), the latter two using MSL with R=40 and antithetics.

Looking first at column (1) that contains the standard probit results for BK, we find that a one percentage point decrease in the proportion of pensioners leads to a reduction in estimated market size that is equal to a population reduction of 3800. The PENSION and YOUTH coefficients however are only marginally significant. More importantly, rival outlets (RIVAL) have a large and significant effect on estimated market size: one rival outlet leads BK to increase its estimate of market size by 80 000 people. This number is close to what would be obtained from the reduced form results if one asked the question: by how much should population increase to yield an equal rise in the entry probability as is the effect of one existing McD outlet? We also find that our controls for market size, the number of own and rival outlets in the neighboring districts

(OWNNB and RIVALNB), both carry significant coefficients in the market size function S(.).

[TABLE V HERE]

We see that AREA has no effect on variable profits, but that WAGE increases them. The number of own outlets increases variable profits, whereas they are decreasing in the number of rival outlets through the negative and significant coefficient on the own outlet-rival outlet interaction. Neither control for market size carries a significant coefficient. Finally, our estimates suggest that fixed costs have increased to 1993.

In column (2) we report the BK results using the random effects probit. For the most part, the results are close to the ML probit results. PENSION in S(.), and WAGE in V(.) are no longer significant; the coefficient of own outlets in V(.) increases from 0.29 to 0.5; and the point estimate of fixed entry costs increases from 1.69 to 2.24. The most notable result is that our point estimate of the coefficient (measure of variance share) of the random effect is highly insignificant (p-value 0.197). The point estimate suggests a variance share of one third. We find no correlation between own existing outlets and the random effect (the μ_{iOWN} in the Error Structure Section of Table V), but the correlation between rival outlets and the random effect (μ_{iRIVAL}) is positive and significant. Note that the introduction of unobserved heterogeneity drives the coefficient of rival outlets in S(.), the market size function, into insignificance (p-value 0.165). As we cannot reject the Null of no unobserved heterogeneity, we conclude that BK uses rival outlets to update its beliefs of market size.

Finally, we estimate the model assuming that unobserved heterogeneity enters in a linearly separable way (i.e., as part of the fixed costs of entry) and present the results in column (3). We find that the statistical significance of coefficients is weaker across the board than in columns (1) and (2). Estimated fixed costs of entry are notably higher (4.17) than before. The signs of the market definition controls in S(.) are reversed. The coefficient of the random effect (s.e.) is 0.907 (0.937), and the coefficient of existing rival outlets in S(.) 0.069 (0.227).

6.3. Leader (McD) Results

All McD results are produced using MSL. As with BK, we estimate the model under standard assumptions about the error term, and also assuming an equi-correlated error structure. Under the standard assumptions, the follower response is simulated; with an equi-correlated structure, both follower response and the time-invariant error term are simulated. In simulating follower response, we employ the BK results obtained using ML, i.e., under the standard assumptions about the error term, since we were unable to reject the Null of the normal error term assumption. The number of simulation draws (R) is again 40.

In column (4) of Table V we present the results assuming a standard probit error structure. We find that the proportion of pensioners has a negative impact on McD's estimated market size: the effect is larger than for BK. Numbers of outlets of either firm in neighboring markets have no impact. In line with BK results, we find that the point estimate of the coefficient of rival outlets is positive (0.96), and highly significant (p-value 0.000). This is evidence that McD uses BK outlets to update its beliefs on market size.

Considering the variable profit function, we find that AREA has no statistically significant impact, but WAGE affects profits positively. Variable profits are increasing in the number of own outlets, and decreasing in the number of rival outlets through the interaction term's negative coefficient. Comparing the effects of outlets on variable profits between the firms, own outlets increase McD profits more than BK's (0.55 against 0.29 in columns (1) and (4)), but McD profits are more sensitive to competition than BK's (interaction term's coefficient –0.11 for McD, -0.01 for BK). Whereas the market definition controls obtained significant coefficients for BK in S(.), they carry significant coefficients for McD in V(.). The signs of the neighborhood variables are what was anticipated: variable profits are increasing in own outlets, and decreasing in rival outlets in neighboring districts. This suggests increasing returns to (network of outlets) scale. Estimated fixed costs do not vary significantly over time, and are slightly larger than those estimated for BK in 1991, but not thereafter (1.91 versus 1.69 respectively).

Turning to the estimations that allow for unobserved heterogeneity, we find in column (5) that the coefficients in S(.) are little affected. The explanation for this is clearly the very low point estimate for ρ_{M0} (0.03). The coefficients in V(.) react somewhat more: the coefficient of own outlets increases to 0.72 (from 0.55), the coefficient of the interaction term is now –0.2. Also, neither of the coefficients controlling for market definition remains significant. The estimate of fixed entry costs changes from 1.91 to 2.11. The random effect is again significantly correlated with rival, but not with own outlets. Importantly, however, our learning result is essentially unchanged: the coefficient of rival outlets in S(.) is now 0.87 (as opposed to 0.96 in column (4)), and significant at the 6% level. Estimating the model with linearly separable random effects (column (6)) shows that unobserved heterogeneity is not important. The point estimate (standard error) of ρ_{M0} is 0.558 (0.503). Our estimates show that the random effect is negatively (but insignificantly) correlated with own, and positively with rival stock of outlets. Most of the (statistically significant) coefficients are very close to those in column (5). The coefficient of rival outlets in S(.), measuring firm learning is 0.778 (s.e. 0.299).

6.4. Summary and Discussion of Structural Results

Estimating a (more) structural model produces substantial additional insights into how the identity of an entrant is established, and how the existing market structure affects entry decisions. The structural estimations reveal that the observed positive relationship between existing rival outlets and entry decisions that was apparent in Figure 1, and confirmed in the reduced form estimations, is not an artifact of spurious state dependence and unobserved heterogeneity. We could not reject the Null of no unobserved heterogeneity in either the reduced or the structural form estimations. The structural estimations also confirm that the positive effect of rival outlets on entry decisions (where significant) is through the firm's estimate of market size; variable profits are decreasing in the number of rival outlets.

Finally, our results show that the two firms' profit functions are rather different. They react differently to exogenous variables, their profits increase at different rates through new outlets, and are differently affected by competition. We found that BK's estimate of market size is less affected by the number of pensioners than McD's and that McD's variable profits increase faster as a function of wages. Baseline fixed costs of entry are somewhat smaller for BK (using the standard probit results), but they have been increasing between 1991 and 1993 whereas McD's have not.

All this suggests that the firms are offering differentiated products. From a more technical point of view, it may be dangerous to impose symmetry upon firms' profit functions even if they seem very similar upon first inspection.

It may seem surprising that firms resort to learning. However this is in line with what our industry sources told us about the firms' entry behavior. Put shortly, McD is regarded as a highly professional and independent organization. BK, in contrast, was reputed to "open its outlets where McD has one". Our results show that part of McD's "professionalism" is that it makes use of information that its rival's behavior generates.

7. CONCLUSIONS

The objective of this paper was to shed light on entry in markets with multi-plant firms (chain stores). The particular questions explored were the identity of the entrant, specifically, whether we are more likely to see new entry by the incumbent or entry by a new firm; and whether existing presence deters entry generally.

We argued in the Introduction that to address these questions optimally requires a data set exhibiting certain characteristics: a clearly defined set of potential firms, a large number of (potential) markets in which conduct is roughly similar, and a sufficiently high volume of entry to provide the econometrician with variation in the dependent variable. We then demonstrated that the UK counter service burger market displays such characteristics. For the period of study, it can be characterized as a duopoly. Fast food is a good sold locally, allowing us to divide the country into local markets. Important decisions on entry and location of outlets, pricing, and types of goods sold are all made centrally, thereby making conduct in different local markets (at least approximately) constant; and the firms in question are actively opening new outlets during the period of study.

In a key departure from the recent empirical entry literature (but motivated by it), we estimate firm-specific equations. The relatively straightforward nature of our industry facilitates this significantly. We find that firms react differently to market characteristics and hence that differentiating between firms is an important flexibility at least with our particular data. The implication is that one should exercise care in imposing parameter values across firms, a practice that is common in the literature, since it may bias results. Unobserved (market-specific) heterogeneity seems not to play an important role in our data.

In addition to market characteristics variables, we employed different market structure variables that allowed us to answer the questions posed at the beginning of this paper. Rival presence lowers variable profits. Estimations of the variable profit function suggest that for both firms, variable profits are increasing in the number of own outlets. Whether this is due to increased market power and higher prices, or greater ability to exploit economies of scale, we cannot tell.

Our most novel finding is that both firms use rival presence to update their expectations of market size upwards. The estimated effects of rival outlets are large and statistically significant. Thus rival presence has two quite different effects upon the profit function. The implied positive (net) effects of rival presence calculated from the reduced form models are comfortingly close to the learning effects identified in the structural models. On the technical side, our structural form estimations showed that it is important to think about the interpretation of unobserved heterogeneity.

Returning to the question posed in the title of the paper, the "beef" is in learning. The two firms we study are large, professionally managed organizations, both of which have invested in honing their skills at opening new outlets. They continue to open outlets at a (worldwide) pace that is unlikely to be exceeded by many other organizations; their products are among the best known by potential consumers, young and old. Nevertheless, our results are not explicable within the traditional theoretical IO framework of Shaked and Sutton (1991) which encompasses a large proportion of the theoretical literature on entry. They are the opposite to what would be observed from an entry prevention strategy. Instead, they indicate strongly that there are positive spillovers to both firms from the presence of the rival in a given market. These spillovers are best explained as the product of learning: firms are uncertain about the true size of a given market, and use the observation of rival presence to update their beliefs. In turn, this, coupled with profit spillovers arising from own presence, goes a long way towards explaining the otherwise puzzling phenomenon of a continuing program of outlet expansion that such chain stores engage in. If these learning effects are indeed of such great importance in this industry, one would expect them to be paramount to firms in similar industries making fewer and less frequent entry decisions.

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Table I
Key Dates in the UK History of Burger Retailing

Date	Event
1960s	Wimpy brand established, later bought by United Biscuits
1970s	Wimpy established counter service
1974	McDonalds opens first store
1983	McDonalds exceeds 100 outlets
1986	Wendy's leaves the UK, selling last 16 restaurants
	McDonalds exceeds 200 outlets
	McDonalds starts to franchise outlets
1988	Burger King brand (at this time small) bought by Grand Met
1990	Burger King has 60 outlets
	Grand Mets burger operations separated into table and counter service
	Counter Service operations mostly rebadged as Burger King
	Wimpy International formed by management buy-out from Grand Met
	Grand Met insists on 3 year agreement preventing Wimpy opening counter service or drive in outlets
1993	June: Grand Met/ Wimpy agreement expires
	Wendy's plans return
	McDonalds has around 500 outlets
1994	Wimpy has 240 outlets, all eat-in
end 1995	Burger King has approx. 300 outlets McDonalds has over 600 outlets
May 1996	Wimpy has 272 outlets
	McDonalds and Burger King each opening around 70 restaurants per year
1998	Wendy's has around 10 outlets

Table II
Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Area (thousand square km)	0.493	0.717	0.015	6.497
Population (thousands)	124.0	94.956	11	1017
Youth (%)	14.0	1.127	7.0	17.0
Pensioners (%)	19.0	3.452	12.0	35.0
Council Tax (£)	419.761	163.724	0	963
Wage (£000)	13.985	1.801	1.085	17.208
Unemployment (%)	6.0	2.386	1.0	26.0
Number of BK neighbors	2.715	3.245	0	37
Number of McD Neighbors	6.641	6.849	0	50

Table III
Statistical Information on Fast Food Outlets

All Districts	BK	McD
Total number of outlets at end of 1995	392	637
Transit outlets	98	45
Three London boroughs	21	27
Total number of exits since chain started	n.k.	4
Estimation Sample (452 Districts, non-transit outlets)	**BK**	**McD**
Stock at end of 1995	273	561
Number of new outlets 1991-1995	175	196
Number of districts entered in 1991-1995	126	148
Proportion of outlets franchised	0.73	0.2

Table IV
Reduced Form Estimations

Variable	BK Results		MCD Results	
	(1) Probit	(2) LPM	(3) Probit	(4) LPM
Constant	-2.0719	-	-1.3434	-
	(1.3640)		(1.0710)	
AREA	0.0905	-	-0.1592	-
	(0.2037)		(0.2185)	
POPAR	-0.4047	-0.0237	0.0499	-0.0057
	(0.2144)	(0.0105)	(0.1955)	(0.0116)
POP	0.5577	0.0815	0.0602	0.0350
	(0.1158)	(0.0083)	(0.0827)	(0.0091)
CTAX	1.2167	0.0880	-0.5926	-0.0815
	(0.7786)	(0.0677)	(0.5883)	(0.0743)
UE	-0.7522	0.1031	0.2498	-0.2951
	(2.7984)	(0.2693)	(2.4173)	(0.2943)
YOUTH	-6.2457	-1.0388	1.4773	0.6735
	(5.4948)	(0.5822)	(.4.7195)	(0.6384)
PENSION	-4.6372	-0.4931	-2.5559	-0.0422
	(2.4640)	(0.2063)	(1.9095)	(0.2258)
WAGE	7.7732	-0.2144	-2.8190	-0.1353
	(5.3838)	(0.3177)	(4.1692)	(0.3470)
LONDON	0.1209	-	-0.3051	-
	(0.2707)		(0.2208)	
RIVALNB	-0.0952	-0.0103	-0.0177	-0.0043
	(0.0204)	(0.0015)	(0.0220)	(0.0031)
OWNNB	0.1672	0.0236	0.0127	0.0006
	(0.0326)	(0.0285)	(0.0121)	(0.0016)

Table IV (Cont.)
Reduced Form Estimations

Variable	BK results		MCD results	
	(1) Probit	(2) LPM	(3) Probit	(4) LPM
M1B0	0.7431	0.0456	0.6147	0.0403
	(0.1845)	(0.0138)	(0.1539)	(0.0031)
M1B1	0.1983	-0.0244	0.7565	0.0525
	(0.2235)	(0.0199)	(0.1901)	(0.0220)
M0B1	0.4534	0.0088	0.54956	0.0346
	(0.2628)	(0.0299)	(0.3005)	(0.0328)
M2B0	1.0277	0.0934	1.2134	0.1405
	(0.2257)	(0.0238)	(0.1899)	(0.0261)
M2B1	0.3977	-0.0001	1.3348	0.1574
	(0.2614)	(0.0258)	(0.1997)	(0.0284)
M0B2	-	-	1.2689	0.1384
			(0.3373)	(0.0530)
M1B2	-	-	1.1200	0.1061
			(0.3718)	(0.0567)
M2B2	-0.1040	-0.0669	1.5330	0.2070
	(0.6196)	(0.0558)	(0.3623)	(0.0610)
M3B0	1.0860	0.1895	-0.1221	-0.0414
	(0.3203)	(0.0406)	(0.2459)	(0.0444)
M3BI	0.2875	-0.0064	1.6081	0.2300
	(0.2514)	(0.0289)	(0.2205)	(0.0318)
MIB3	-0.14862	0.0421	-	-
	(0.8860)	(0.0788)		
ρ	0.000001	-	a	-
	(2.2873)			
nobs	2260	2260	2260	2260
LogL.	-426.7804		-518.7245	
T1	286.6701	7.35	233.3060	5.61
	(28)	(54,2206)	(28)	(55,2204)
T2	56.4728 (9)	5.3665	81.7388	7.8536
		(9,2214)	(10)	(10,2214)
T3		0.694	-	0.688
		(32,2206)		(32,2205)
(pseudo) R^2	0.2514	0.1526	0.1836	0.1227

Notes: Numbers given are coefficient and (standard error). Estimations include year dummies (some significant in the case of BK) and dummies for missing data cases described in the text, Section 4.2.

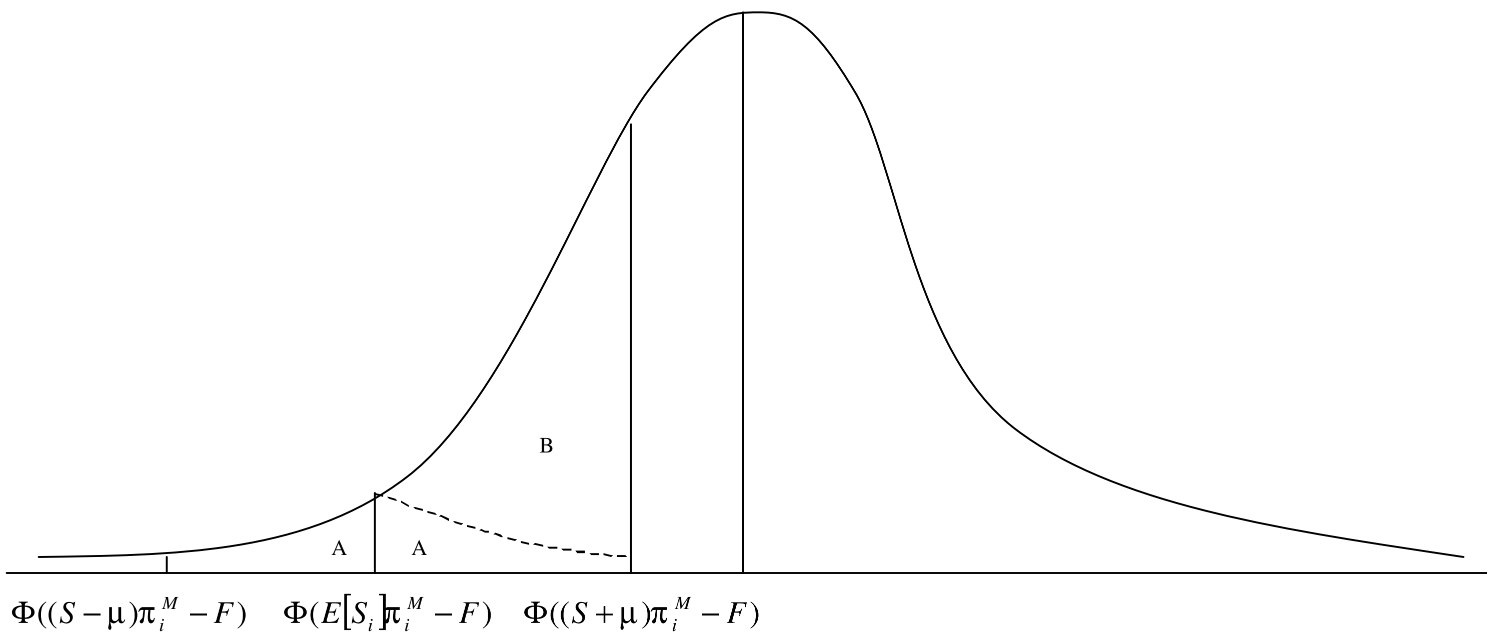
T1 = LR-test (probit) or F-test (LPM) of joint significance of RHS variables (d.f.).
T2 = LR-test (probit or F-test (LPM) of joint significant of market structure variables (d.f.).
T3 = F-test of fixed effects (LPM) (d.f.).
[a] For probit estimations, the ratio between the individual (random effect) and common error terms' variance was <.001, and the random effect was therefore excluded.
Pseudo R^2 for probit is calculated as $1-(L_1/L_0)$, as recommended by Cameron and Windmeijer (1997).

Table V
Structural Estimations

Function/ variable	(1) BK Standard Probit	(2) BK Equi-correlated Probit Non-linear Unobserved Heterog.	(3) BK Equi-correlated Probit: Linear Unobserved Heterog.	(4) MCD Standard Probit	(5) MCD Equi-correlated Probit Non-linear Unobserved Heterog.	(6) MCD Equi-correlated Probit Linear Unobserved Heterog.
Market Size						
β_{i1} / YOUTH	-5.6132	-5.3092	-0.9877	1.5260	1.7998	1.3683
	(3.3906)	(5.1556)	(.3.8666)	(2.9520)	(3.1473)	(2.8202)
β_{i2} / PENSION	-3.8465	-3.5995	-0.8218	-5.7405	-5.3 473	-5.8966
	(2.0658)	(2.9652)	(2.3647)	(2.0462)	(1.9706)	(1.9987)
θ_{iS2} / RIVAL	0.8038	0.3641	0.0693	0.9631	0.8737	0.7779
	(0.2183)	(0.2624)	(0.2268)	(0.2353)	(0.4599)	(0.2988)
θ_{iS3} / OWNNB	0.4241	0.5408	0.6037	0.0157	0.0010	0.0145
	(0.0896)	(0.1115)	(0.1182)	(0.0198)	(0.0198)	(0.0189)
θ_{iS4} / RIVALNB	-0.1774	-0.2415	-0.2589	-0.0394	-0.0268	-0.0273
	(0.0353)	(0.0492)	(0.0524)	(0.0398)	(0.0410)	(0.0385)
Variable Profits						
γ_{i1} / AREA	-0.0915	-0.3026	-1.4287	0.0309	0.0071	0.1807
	(0.2269)	(0.3577)	(0.9408)	(0.5099)	(0.5422)	(0.7514)
γ_{i2} / WAGE	0.5171	0.7820	1.1007	0.6908	0.5455	0.6326
	(0.1345)	(0.4586)	(0.6253)	(0.3571)	(0.3869)	(0.4874)
θ_{iV1} / OWN	0.2851	0.5011	0.8270	0.5497	0.7183	0.7556
	(0.0693)	(0.1722)	(0.4810)	(0.0860)	(0.1351)	(0.1975)
θ_{iV2} / RIVAL	-0.0239	0.2327	0.4104	-0.0376	0.0025	0.0883
	(0.0467)	(0.2108)	(0.2899)	(0.1591)	(0.2975)	(0.3181)
θ_{iV3}/ OWN*RIVAL	-0.0127	-0.0242	-0.0241	-0.1056	-0.2026	-0.2014
	(0.0061)	(0.0267)	(0.0511)	(0.0254)	(0.0636)	(0.0717)
θ_{iV4} / OWNNB	-0.0381	-0.0887	-0.0933	0.1838	0.2018	0.2716
	(0.0300)	(0.0560)	(0.0638)	(0.0860)	(0.1346)	(0.1476)
θ_{iV5} / RIVALNB	-0.0147	-0.0394	-0.0783	-0.3739	-0.3566	-0.5061
	(0.0146)	(0.0393)	(0.0562)	(0.1903)	(0.2390)	(0.2977)
Fixed Entry Costs						
δ_{i0}	1.6890	2.2398	4.1718	1.9149	2.1084	2.1380
	(0.2185)	(0.5413)	(1.9684)	(0.1834)	(0.3399)	(0.4250)
δ_{i92}	0.6065	0.9829	1.5100	0.2667	0.2954	0.3244
	(0.1764)	(0.4267)	(0.8872)	(0.1816)	(0.1974)	(0.2244)
δ_{i93}	0.3719	0.6400	0.9299	0.0806	0.0926	0.1349
	(0.1640)	(0.3555)	(0.6883)	(0.1672)	(0.1775)	(0.1916)
δ_{i94}	0.1996	0.2273	0.3442	-0.0759	-0.1055	-0.0968
	(0.1465)	(0.2812)	(0.4889)	(0.1604)	(0.1693)	(0.1790)
δ_{i95}	0.0365	-0.0147	0.1844	0.2356	0.2655	0.2985
	(0.1505)	(0.2652)	(0.4287)	(0.1761)	(0.1915)	(0.2120)
Error Structure						
ρ_{i0}	-	0.5133	0.9071	-	0.0262	0.5581
		(0.3976)	(0.9367)		(0.7212)	(0.5031)
μ_{iOWN}	-	-0.3730	-0.5328	-	-0.0976	-0.1555
		(0.2880)	(0.3495)		(0.1606)	(0.1711)
μ_{iRIVAL}	-	0.5187	0.8861	-	0.5294	0.2988
		(0.1987)	(0.3734)		(0.2872)	(0.2499)
Nobs.	2260	2260	2260	2260	2260	2260
LogL.	-421.5593	-423.1307	-419.2788	-536.9453	-535.5359	-534.6723
Estimation method	ML	MSL	MSL	MSL	MSL	MSL
# simulations	-	40	40	40	40	40

NOTES: All simulation estimators use antithetics.

FIGURE 1



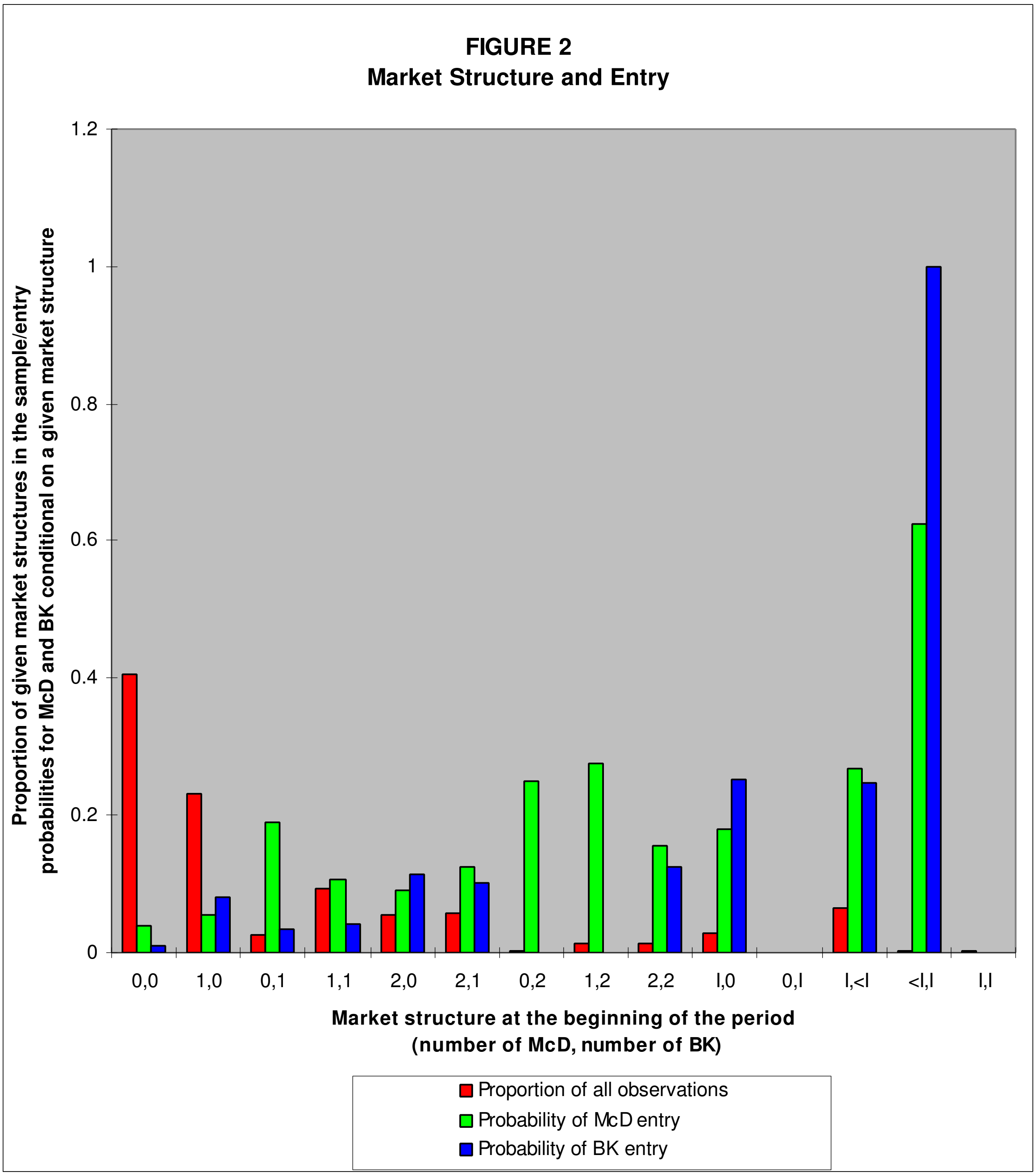


FIGURE 2
Market Structure and Entry
Proportion of given market structures in the sample/entry probabilities for McD and BK conditional on a given market structure
1.2
1
0.8
0.6
0.4
0.2
0
0,0
1,0
0,1
1,1
2,0
2,1
0,2
1,2
2,2
I,0
0,I
I,<I
<I,I
I,I
Market structure at the beginning of the period
(number of McD, number of BK)
Proportion of all observations
Probability of McD entry
Probability of BK entry

FOOTNOTES:

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2 Wheaton (1987) documents that in the U.S also, period to period entry decisions are unlikely. According to him, there is a planning lag of 18 to 24 months between obtaining a construction permit and completion of an office building. The lags are presumably shorter for those new outlets that are opened in old buildings.

3 Alternatively, particular features of the market may yield the follower profits that are so much higher (due to product differentiation) than the first period monopoly profits of the leader (plus the expected discounted profits from the second period) that an identical cost shock for each renders monopoly entry of the leader unprofitable, yet still results in positive monopoly profits for the follower.

4 To see how, imagine that in Figure 1 the positive population shock would be exactly large enough to take the entry probability under a positive shock to the mean of the distribution of ε_{it}; the linear combination of the entry probabilities of this and (any) negative shock would be larger than the entry probability at the expected population size even though $\Phi(.)$ is not convex round its mean.

5 Table I shows that Wimpy has only modestly increased its number of outlets since the expiry of the agreement with Grand Met. An interesting parallel exists in electricity generation in the UK. The two

strategic players are National Power and Powergen, whilst the third player, Nuclear Electric, takes a non-strategic role. This has successfully been modeled as a duopoly by authors such as Green and Newbery (1992).

6 In previous versions, we used a data set of 453 markets. A check revealed that we had included the Isles of Scilly (off the South-West corner of England) into the data set. They clearly are a non-viable market and were therefore excluded.

7 Analysis of the data reveals that of 2,260 observations, BK has multiple entry only 15 times (12 times with 2, 3 times with 3 outlets) whereas the corresponding number for McD is 13 (all with 2 outlets).

8 We used end of period market structures in order to include entry from our last observation period.

9 We note that a large population is not necessary condition for entry. London's City of Westminster, with a population of less than 6 000, has the largest number of outlets for both firms. It is however excluded from the estimation sample together with two other London districts (City of London, and Kensington and Chelsea). The reason for this is that for all three districts, the daytime population is significantly higher than the resident population.

10 See Toivanen and Waterson (2000) for one solution to this problem.

11 This could, in a relatively straightforward manner, be extended to firms deciding how many new outlets to open. Given our data (see Section 3), the simpler framework captures the essential decision here.

12 An alternative approach would be to follow BR and assume that firms make entry and continuation decisions each period. One would then estimate an ordered probit, possibly using the number of rival outlets as an (endogenous) explanatory variable. We argue that the decision to open an outlet is significantly different from the decision to keep an existing outlet open.

13 Davis (1999) develops a technique that allows the estimation of multiplant firms' entry decisions. His model however assumes that firms produce homogenous goods.

14 If we were to observe $\theta_{Si}<0$, this would indicate that firms have systematically entered markets that are smaller than expected.

15 See also Berry (1992) for an application to firm entry; Hyslop (1999) for a recent application to panel data and spurious state dependence; and the seminal papers by McFadden (1989) and Pakes and Pollard, (1989) for the asymptotic theory of simulation estimators.

16 This is necessary when we simulate BK responses to leader (McD) entry decisions (see below).

17 We find this interpretation less plausible. Also, as our interest is in the effect of rival outlets on own entry, including the random effect into the market share function allows us to better control for the possibility that the positive correlation between own entry and rival outlets noted in Figure 2 is due to unobservables.

18 We employ the standard quadrature method (with 20 evaluation points) suggested by Butler and Moffit (1982) to estimate the random effects probit.

19 The quarters are ranked ascendingly in the number of outlets opened for each year, and – for what it is worth given the small sample – the differences in the mean number of outlets opened in a quarter are significant at the 4% (or higher) level. These patterns are, if anything, stronger within our sample period.