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Market structure and entry: where's the beef?

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We study the effects of market structure on entry using data from the U.K. fast food (counter-service burger) industry over the years 1991–1995, for which the market can be characterized as a duopoly. We use both reduced-form estimations and a structural model, controlling for market-specific time-invariant unobservables. For both firms, we find that market structure matters greatly. Specifically, rival presence increases the probability of entry by increasing expected market size, whereas variable profits per customer are increasing in the number of own outlets. Our results suggest the presence of product differentiation, firm learning, and market power.

1. Introduction

■ The development of chain stores provides a useful context in which to examine multiproduct firms and entry. Of particular interest is whether we are more likely to see the incumbent firm opening a new store than to see the entry of a new firm. The standard model of entry excludes the effects of learning and predicts that, all else equal, when a firm has the choice between two otherwise identical markets but faces competition in only one, it will enter the monopoly market. Entry deterrence would exacerbate this. However, if the potential entrant can learn about the profitability of a market by observing the existing rival's performance, is it possible that this prediction may be reversed? We attempt to answer these questions by empirically analyzing the development of market structures in the U.K. counter-service burger industry using a panel of entry data.

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Over the time period 1991–1995, this market has some attractive features. First, the market is well defined in terms of the goods the firms produce, and these are reasonably close substitutes. Second, due to the centralized operations of the main firms, the locations and opening dates of outlets, their exact specifications, types of goods sold, and pricing policies are largely decided centrally, and within each chain the outlets are reasonably homogeneous in type. Third, the firms in question have aggressive expansion policies. Fourth, geographical and demographic data are available that relate to areas that 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, as 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.

Importantly, our data reveal that exit, i.e., closure of outlets, is a rare occurrence for the duopolists. This, together with an annual planning round for the firms and U.K. planning permits that put a premium on retaining sites, allows us to treat existing outlets differently from "new" entries, namely as predetermined variables embodying some sunk costs and thereby affecting both firms' profitability of entry. Thus, we have a number of markets across which the same players operate but between which characteristics vary widely. In sum, the industry is straightforward enough to enable a detailed analysis of the players.

Recently, economists' interest in strategic aspects of firms' entry decisions has taken a turn from purely theoretical analyses (e.g., Dixit, 1979) toward empirical analyses of firms' actual entry or exit decisions, including Bresnahan and Reiss (1991), Berry (1992), and Seim (2002).[1] Bresnahan and Reiss study the market structure of homogeneous-goods industries in isolated Midwestern towns. They infer the level of competition from the entry thresholds that they estimate. Berry estimates entry decisions on airline routes. He makes assumptions about the move order of firms, an approach we utilize below. Many of these articles, however, either downplay the strategic issues relating to entry decisions or use computationally involved methods that allow the researcher to identify only the "average" strategic effect. Davis (1999), in which the author develops a technique that allows the estimation of multiplant firms' entry decisions, is close to our setting, where firms may have several outlets in a given market. However, he assumes that firms produce homogeneous goods. Whereas we take the qualities of the firms as given, Mazzeo (2002) presents a model with product differentiation where the firm can choose quality (though with homogeneity across firms within quality levels) and estimates it using cross-sectional data on roadside motels in the United States.[2] Seim (2002) uses data on local video stores to estimate a model of product differentiation through location choice. She assumes that firms have incomplete information about each other's profitability. Except for Chevalier (1995), Scott Morton (1999), and the version of Berry's model where incumbents move first, these studies treat the "entry" of *existing* firms (i.e., the continuation of operations) as identical to "true" entry of new firms to a given market. Also, none considers the effects of learning. We follow the cited articles 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 articles, our market is a multiplant duopoly, where the same two firms are (potentially at least) active in each of the markets. This last feature allows us to answer the key questions that have remained unanswered in previous empirical studies. In particular, we are able to allow 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.

The remainder of the article is organized as follows: in Section 2 we summarize the relevant theoretical literature and its predictions, and we discuss an extension of the basic econometric

[1] There is also a marketing literature on entry: see, e.g., Geisel, Narasimhan, and Sen (1993) and an organizational learning literature that we draw upon below.

[2] Although our model allows between-firm product differentiation, it does not allow within-firm, between-market product differentiation.

entry model that incorporates firm learning alongside more traditional factors. In Section 3 we present the main features of the market and the data. In particular, we explain the market definition used and provide evidence that supports our decision to treat the industry as a duopoly. Section 4 covers the results from a reduced-form approach to estimation, while Section 5 details our structural estimation strategy and results. Finally, Section 6 offers some concluding comments.

2. The modelling approach

■ **Existing theory.** 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 in market j if

$$E(\Pi_{ij}) - F_{ij} \geq 0. \tag{1}$$

Equation (1) ignores all dynamics and business-stealing effects (e.g., effects on subsequent actions and effects on profits of other own outlets). The early game-theoretic literature on entry, e.g., Dixit (1979), concentrated on analyses of entry prevention and accommodation. Shaked and Sutton (1990) offer a useful presentation in terms of potentially observable variables. The standard theory predicts a negative relation between the 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.

From an institutional ecology or organizational learning perspective, significant spillover effects may occur, meaning that a positive link may exist between an own store and rival entry. As Baum, Li, and Usher (2000, p. 774) put it, "organizations learn vicariously, imitating or avoiding specific actions or practices ... For expanding chains, location choices of large chains may be a particularly important source of information to reduce uncertainty about locations that can support growth." Caplin and Leahy (1998) also 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 also predicts that rival presence has a positive effect on probability of own entry.[3] These hypotheses should be distinguished from an alternative, namely demand heterogeneity. If we measure demand characteristics poorly, i.e., if there are market-specific unobservables, there may be greater or lesser entry into a district than we expect. This is, however, something that we can and do attempt to control for econometrically.

□ **The model.** Our 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 in a given market.[4] 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. Alternatively, one can view the profits (gross of entry costs) as expected discounted profits, although this necessitates the further assumption that firms are myopic in their entry decisions and do not take into account the effects that current entry decisions have on future entry decisions. We control to some extent for the static nature of our model by conditioning entry decisions on existing market structure, i.e., past entry decisions. The form of second-stage competition is assumed to be common knowledge among the potential entrants.

[3] Caplin and Leahy also discuss a crowd externality, where the existence of other shops' customers makes a location more attractive to shops that are not directly competing with the existing shops (e.g., furniture shops and fast food outlets). However, it is unlikely that crowd externalities would be created by one burger outlet for another. Similarly, customer-based learning might take place, meaning existing own presence increases the probability of own (additional) entry. In the case of our product and time period, such learning has most likely already happened.

[4] This could 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.

To operationalize the model, we assume that the (reduced-form) profit function of firm i in market j in period t, resulting from competition in the second stage of the model, is of the form

$$\Pi_{ijt}(\chi_{ijt}; Own_{jt-1}, Rival_{jt}) = \pi_{ijt}(Own_{jt-1} + \chi_{ijt}, Rival_{jt}) - (F_{ijt}(Own_{jt-1}) + \varepsilon_{ijt})\chi_{ijt}, \quad (2)$$

where $\pi(\cdot)$ is reduced-form profits gross of entry costs, $F(\cdot)$ denotes the fixed entry costs (possibly unobserved by the econometrician), and ε_{ijt} is the period- and firm-specific (independently and identically normally distributed, common knowledge) shock to these costs. The choice variable $\chi_{ijt} \in \{0, 1\}$ is defined as the decision (not) to open a new outlet. The variable Own_{jt} ($Rival_{jt}$) denotes the number of own (rival) outlets by the end of period t. The functions $\pi(\cdot)$ and $F(\cdot)$ may also contain market- and firm-specific, possibly time-varying, variables representing underlying measures of profitability such as market size. At least some part of the entry cost is sunk, i.e., only incurred at entry.[5]

Consider first the problem of a single "myopic" firm deciding whether or not to enter a market for the first time. Being myopic means that the firm assumes that the number of rival stores stays constant, i.e., the number of rival outlets at the end of period t is the same as at the end of the previous period ($Rival_{jt} = Rival_{jt-1}$). The firm will then enter if and only if

$$\Pi_{ijt}(1; 0, Rival_{jt}) = \pi_{ijt}(1, Rival_{jt}) - F_{ijt}(1) - \varepsilon_{ijt} > 0. \quad (3)$$

Here we have normalized the profits from having no outlets to zero. It is straightforward to generalize (3) to subsequent outlets and show that (a myopic) firm's decision rule is given by "enter if and only if

$$\Pi_{ijt}(1; Own_{jt-1}, Rival_{jt}) > \Pi_{ijt}(0; Own_{jt-1}, Rival_{jt})." \quad (4)$$

The firm takes into account the profit difference between operating n stores and the (forgone) profits of operating the old number of stores ($n - 1$), and the fixed costs of opening the new store.

Modelling strategic entry decisions is more problematic, as shown in the seminal contributions of Bresnahan and Reiss (e.g., 1991), because the equilibrium response of the rival matters. As they show, one cannot econometrically model a simultaneous-move entry game as a system of simultaneous equations, because the equilibrium configurations are not unique. However, we assume, as does Berry (1992), that firms make their entry decisions sequentially. Thus the follower takes the leader's decision as given, and the value it assigns to $Rival_{jt}$ 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., $Rival_{jt} = Rival(Own_{jt})$. We adopt this approach because it seems reasonable to assume (see the next section) that one of the firms acts as a leader. The leader's entry decision is accordingly given by

$$\Pi_{ijt}(1; Own_{jt-1}, Rival(Own_{jt}, Own_{jt-1} + 1),) > \Pi_{ijt}(0; Own_{jt-1}, Rival(Own_{jt}, Own_{jt-1})), \quad (5)$$

where the notation makes clear that rival entry depends both on own lagged outlets (the learning effect) and actual outlets (the strategic effect). The previous section suggested that if firm learning effects are present, a firm's estimate of expected profits is affected by the number of existing rival outlets. Notice we assume that the leader-follower timing applies to entry decisions within each period; the follower cannot learn from the outlets the leader is opening that period, only from those opened in previous periods.

At its simplest, our modelling structure allows us to employ standard ML (probit) estimation methods; the only added complication is that we must take into account that the objective function is different for markets where the firm has own existing outlets. We detail in Section 5 how we

[5] Our econometric model does not allow us to separately identify entry costs from fixed costs that have to be incurred every period if operations are continued, if the latter are a function of the number of outlets.

allow for unobserved heterogeneity, and how we deal with the leader-follower structure of the model.

3. The development of the U.K. fast food market, and the data

■ **The market definition.** The market we study is an essentially local counter-service market. Counter service is significantly different from table service. We also distinguish this everyday market from the *transit* market, a relatively recent phenomenon in which Burger King (particularly) operates from motorway service areas, etc. In this respect the U.K. fast food market differs from the U.S. market, where many fast food outlets are transit outlets. The local market is influenced by local characteristics such as population, economic activity, etc. Thus our ideal unit of observation is the local market, also the observation unit of Bresnahan and Reiss and, e.g., Kalnins and Lafontaine (2004). People in Britain do not travel far to satisfy their fast food needs. We therefore choose the unit of observation to be local authority districts, of which there are almost 500 in Great Britain. Our presumption is that people (save those near a boundary) seldom travel outside their district in search of fast food.[6]

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

Traditionally (and as recently as 30 years ago), small, unbranded local suppliers dominated the U.K. fast food market.[7] This has now changed rapidly as a result of entry by burger, chicken, and pizza chains, with burger chains being the most important. Three players dominate the burger market: McD, BK, and Wimpy, with sales shares estimated by 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 U.K.[8]

In terms of expansion, 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 that prevented Wimpy opening any counter-service or drive-through outlets (MAP, 1994). Consequently, Wimpy's image suffered from a forced reliance on table service and the inability to compete 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 £.5 million, against £27.3 million for McD and £6.7 million for BK. The year 1994 (the first year after the agreement between Wimpy and Grand Met had expired), has McD spending £31.3 million, BK spending £8.2 million, and Wimpy £.6 million, and later years show a similar picture, with Wimpy's expenditure averaging around a tenth of BK's over the 1990s (data from MEAL, various years). All its 240 outlets were table

[6] 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. These observations are also consistent with Thomadsen's (2000) remarks concerning the market area in the United States, which would suggest by calculation that almost all our districts are at least large enough to constitute markets.

[7] Many of these were "fish and chip" shops, supplying a significantly different product. Fish and chip sales are concentrated at particular times of day, early lunchtime and evening, and do not normally operate outside those times. By contrast, burger outlets open from around 9:00 A.M. and supply continually until mid or late evening. Fish and chip outlets seldom incorporate seating.

[8] Burger operators successful in other countries, including Wendy's and Quick Burger, have failed to establish a U.K. foothold. There are smaller chains of limited impact, the most important being Starburger (with around 60 outlets compared with over 400 for BK and 600 for McD in 1995), and some strictly local outlets, but barriers to the entry of new large chains are likely to be significant.

service (and therefore outside our defined market) in 1994, and by mid-1996 it had grown to only 272 outlets, largely by developing at service stations (*Financial Times*, various years). By contrast, BK, 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 renaming former Wimpy outlets, was complete late in 1990, and local market growth since then has largely been organic. The two firms we examine hold a combined share of 75% in the relevant counter-service market. Thus, there are only two strategic players over our period, BK and McD. Based on its earlier start and larger share, plus our 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 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 Creutzfeld-Jacob Disease ("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.

□ **Data.** Briefly, the basic data on store locations and openings come, in McDonalds' case, entirely from the company itself. These data are high quality and useful for other reasons. For example, they establish that exit is an unusual phenomenon. In the case of Burger King, the data come from a variety of sources, although we do have a complete listing of stores in 1995 from the company itself. 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 the U.K. government publication *Regional Trends*, the only consistent source of annual data at this level of aggregation, supplemented by rating data from the government's Valuation Office Agency. These data sources on outlets and on demographics are matched using a package available to U.K. academic sources called "Postzon," which is based on U.K. postcodes. A further source (the Automobile Association's package "A to B") yields distances between districts. More detail on construction of each of the variables, including definitions, sources and problems, is given in the Data Appendix (www.rje.org/main/sup-mat.html).

The estimation sample consists of five annual observations each for 452 districts—we exclude Northern Ireland, all islands apart from the Isle of Wight, and three inner London boroughs. For each such district market, we observe the geographical area and population, the proportion in various age bands, the council tax rate, average male wage rate (at regional level), and unemployment rate. The extent of commercial activity is given by the sum of business-ratable values for the area. We also observe market structure at the beginning of the period, and whether or not entry by one or the other firm occurred during each year. In addition, we know the distance from the market to the headquarters of both firms, and we calculate the number of outlets of both firms in the neighboring market areas. Most of the data are annual; business-ratable values are updated only every five years. The descriptive statistics of the sample are given in Table 1.

As the descriptive statistics reveal, the markets are heterogeneous. For example, population varies between 11,000 and 1,000,000-plus. Commercial activity as measured by business rates also varies; in fact, it is highly correlated with population over the sample ($r = .866$), but with some clear outliers in major centers such as Manchester. The furthest market is 674 miles from McDonalds' headquarters. Other features of the markets also vary substantially, with youths making up as much as one-third and as little as 14% of specific markets. Predictably, the changes over time are relatively modest for most variables, e.g., population growth is on average less than 500 per annum. Given the heterogeneity, one would expect considerable variation in market structures and observed entry patterns, and this is what we see.

In Table 2 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 and both were growing fast. Our sample includes

TABLE 1 **Descriptive Statistics on Local Authority Districts**

Variable	Mean	Standard Deviation	Minimum	Maximum
Area (thousand square km)	.493	.717	.015	6.497
Population (thousands)	124.170	94.917	10.6	1017.0
Business (Nondomestic) ratable value (£ billion)	72.101	75.742	5.019	641.826
Council tax (£)	418.46	163.35	.00	963.00
Unemployment (%)	3.930	1.443	.64	15.18
Children (%)	12.585	1.029	8.782	16.012
Young adults (%)	20.551	2.662	13.678	35.474
Pensioners (%)	17.817	1.730	12.098	22.796
Average weekly male wages, £	333.02	40.51	246.30	555.80
Number of BK neighbors	2.715	3.245	0	37
Number of McD neighbors	6.641	6.849	0	50

a larger proportion of McD than BK outlets: the main explanation for this lies in the 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.[9]

TABLE 2 **Statistical Information on Fast Food Outlets**

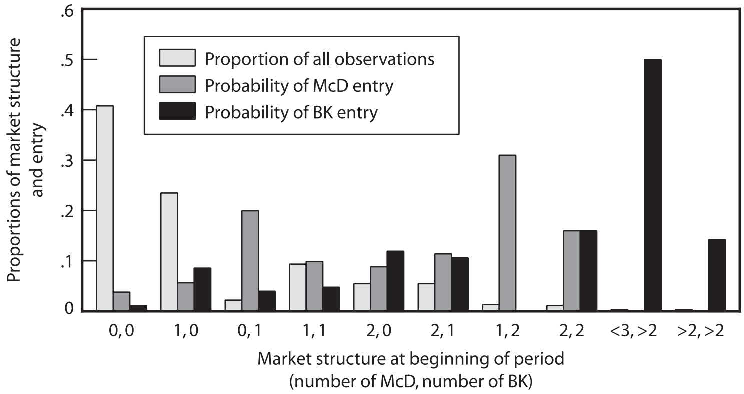
All Districts	BK	McD
Total number of outlets at end of 1995	392	637
Transit outlets	98	45
Three London boroughs	21	27
Total number of exits since chain started	N.K.	4
Estimation sample		
(452 districts, nontransit outlets)		
Stock at end of 1995	273	561
Number of new outlets 1991–1995	175	196
Number of districts entered in 1991–1995	126	148
Proportion of outlets franchised	.73	.2
Mean number of outlets/district by		
beginning of year		
1991	.217	.809
	(.477)	(1.085)
1992	.316	.905
	(.595)	(1.229)
1993	.354	.976
	(.655)	(1.309)
1994	.416	1.073
	(.747)	(1.396)
1995	.487	1.175
	(.854)	(1.473)
End of 1995	.603	1.239
	(.975)	(1.522)

Standard deviations in parentheses.

[9] Both companies are known for their degree of centralization and control over such things as new outlet locations. For example, McD allocates franchisees to stores they are developing. Thus, so far as restrictions on future entry are concerned, there is no particular difference between franchised and managed stores, and we do not distinguish them in our estimations.

FIGURE 1

MARKET STRUCTURE AND ENTRY



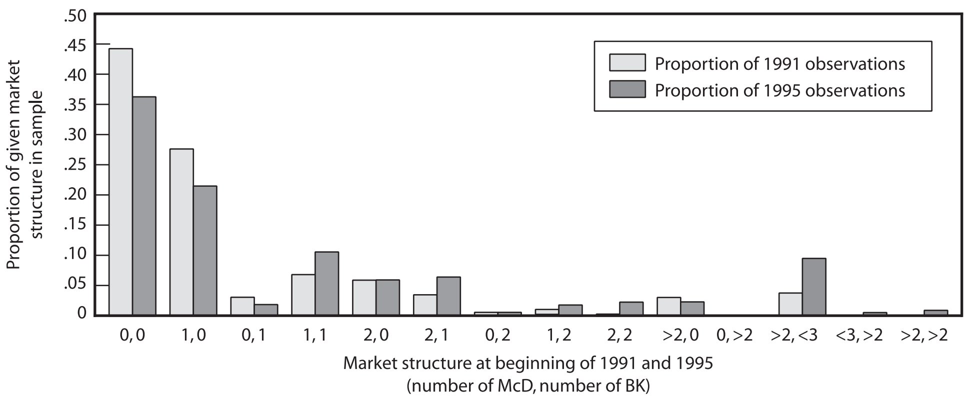
Let us take a first look at the market structure and entry data. In Figure 1 we detail the proportions in which different market structures are observed and display the firms' entry behavior conditional on market structure. A code (M, B) refers to a market structure in which McD has M and BK has B outlets at the beginning of the period. Some market structures (e.g., (0, 3)) are never observed in the data, and others appear infrequently. We have therefore included as final categories several market structures wrapup in which both firms have a number of outlets and entry takes place (labelled (> 3, < 2) and (> 2, > 2)). The largest number of outlets in a market (as of the beginning of a period) observed is 14 for McD, 7 for BK.

Two observations can be made, keeping in mind that Figure 1 entry probabilities are conditioned only on existing market structure. First, 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, 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%. Figure 2 displays the evolution of the market structure distribution over time. As one can see, the proportion of markets with no or only one firm is declining, and that of market structures with multiple outlets by one or both firms is increasing. The proportion of (0, 0), (1, 0), and (0, 1) markets goes down by 15 percentage points.

In our econometric model, we specify our dependent variable as "entry by firm i into market j in period t." Hence we do not differentiate between the opening of one and the opening of

FIGURE

DEVELOPMENT OF THE DISTRIBUTION OF MARKET STRUCTURES, 1991–1995



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.[10] We observe 183 entries thus defined for McD, 157 for BK. For BK, there are a few (14) outlets for which we did not obtain the entry date. In these cases, we treat the outlet as if it was opened prior to our observation period, and attach a dummy to it.[11] There are 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 five cases are where one or the other firm opens two outlets, and the rival opens one outlet.

We have also cross-tabulated the market structure *at the end* of 1995 with population (as in Bresnahan and Reiss, 1991).[12] We found that the smallest market population for which there exists a McD outlet is 41,300 (137 districts are below this threshold); for BK the figure stands at 53,900 (262 districts). We therefore explore below the effects of excluding some markets from the sample.

4. A reduced-form approach

■ **The model.** We first present reduced-form estimation results and then discuss robustness tests based upon them. We estimate the following reduced-form entry function as suggested by Berry (1992) and Reiss (1996):

$$\Pi_{ijt} = X_{ijt}\beta_i + g(Own_{jt}, Rival_{jt}, \theta_i) + \nu_{ijt}. \tag{6}$$

Subscript i denotes firm ($i \in \{M, B\}$, where M stands for McD and B for BK), j the market, and t the time period; the vector X_{ijt} includes market- and firm-specific variables relating to market attractiveness; $g(\cdot)$ is a function of existing Own_{jt} and $Rival_{jt}$ outlets in market j (see also Mazzeo, 2002); and β_i and θ_i are vectors of firm-specific parameters to be estimated. We explore different ways of measuring market structure. In addition to the usual problems with reduced form, an additional problem is that (6) does not allow a rich way to control for multioutlet firms' opportunity costs 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 $Own_{jt} > 0$, the opportunity cost is nonzero (see Toivanen and Waterson (2000) for one solution to this problem). 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. It is a maintained hypothesis throughout that decisions are taken in every region in every time period; one clear alternative would be to view the decision as one of which markets to enter in a given year, given some firm-level constraint on the number of outlets that can be opened simultaneously (or an assumption of total costs of opening outlets being convex in the number of outlets).[13]

We report probit results for both firms. We employ a firm and market random-effects estimator to control for unobserved heterogeneity.[14] In these estimations, we do not control for correlation between unobserved heterogeneity and observables, but in robustness tests we employ estimators that are robust to such correlation.

We include the following variables in the X_{ijt} vector of equation (6): *Area* (thousands of square kilometers), *Population* (which in all estimations is measured in 100,000s), their

[10] Of 2,260 observations, BK has multiple entry only 15 times (12 times with 2 outlets, 3 times with 3 outlets), whereas the corresponding number for McD is 13 (all with 2 outlets).

[11] Omitting the relevant districts from the estimation sample made no difference to the results.

[12] We used end-of-period market structures in order to include entry from our last observation period.

[13] This point is emphasized by the fact that our model, like those in the existing literature, relies on markets being in equilibrium. One could question whether this assumption is supported by our data, as the firms are rapidly expanding during our observation period.

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

interaction, the aggregate of business-ratable values (*BusRate*) for the district (in £ billion), *Council Tax* (measured in thousands of pounds; our proxy for real estate costs), the *Unemployment rate*, the proportion of under 16-year-olds (*Youth*) and the proportion of pensioners (*Pension*), *Wage* (measured in £100,000 per annum; to control for wage costs/average income), *Distance* from the respective head office (miles by road), and dummies for markets within London and bordering one or more London markets (*London*). In addition, we include a full set of time dummies and a dummy for those markets with missing BK opening dates.

The market-structure function $g(\cdot)$ makes use of the indicators used in constructing Figure 1, where variable name Mi, Bk indicates a market structure with i McD outlets and k BK outlets at the beginning of the period.[15] The omitted market structure is a market with no existing outlets of either firm. Finally, we include as control variables for market definition and other informational effects 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).

□ **Results.** We first look at the market characteristics results in Table 3. For BK, we find that *Area* and *Population* carry insignificant coefficients, *BusRate* and *Council Tax* significant positive coefficients, and the *Population∗Area* interaction a negative and significant coefficient. We find that *BusRate* and *Pension* appear to affect McD's entry decisions.[16] Our own-neighbor variable obtains a significant coefficient for BK.

The variables of most interest are the market structure variables. These are presented in Table 4 in the form of marginal effects. Looking first at BK, we find that all the market structure variables except $M2$, $B1$ characterizing structures where McD has more outlets than BK obtain positive and significant marginal effects (and coefficients). For McD we observe that almost all market structure dummies obtain a positive and significant marginal effect. BK is thus—*ceteris paribus*—consistently more likely to enter a market where McD is larger than itself than a market with no outlets of either firm. McD is more likely to enter markets containing other outlets than comparable new markets.

With the caveat that unobservables may be driving our results, 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, since it would lead not only to increased hamburger consumption in general, but also to increased consumption of the firm's own hamburgers. In our view, the most plausible explanation of the pattern of results is therefore firm learning or spillover effects from the other player. The results also suggest that learning effects are strong enough to dominate any negative effects that competition between firms may have on entry decisions. We explore the robustness of our results (to unobservables) below.

□ **Robustness checks.** Clearly, a major issue is whether these somewhat surprising results arise because of unobserved heterogeneity or another specification issue rather than real effects. We therefore engage in an extensive investigation of robustness; for brevity we do not report all the details.[17]

The first issue concerns unobservables and their possible correlation with explanatory variables. We estimated both a linear probability model (LPM) using a Within (fixed-effects) estimator and Chamberlain's (1980) fixed-effects logit, both of which are robust to correlation between explanatory variables and the unobserved heterogeneity terms. These controls did not

[15] The vectors of market structure dummies employed differ between the firms 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). For example, we excluded the dummies $M0$, $B2$ and $M1$, $B2$ from the BK estimation because there was no BK entry into such markets during our observation period.

[16] We are unsurprised by the insignificant coefficient for *Population*, given the variable's high correlation with *BusRate*. The negative coefficient for *Pension* is consistent with consumer surveys in the U.K. that find pensioners less likely than any other group to visit a burger outlet; see Mintel (1998).

[17] Results are available from the authors upon request.

TABLE 3 Reduced-Form Random-Effects Probit Estimations

Variable	BK	McD
Constant	−2.9876***	−1.4932***
	(.6152)	(.5879)
Area	.1042	−.2620
	(.2011)	(.2300)
Population	.6335	.5319
	(.5405)	(.5164)
Population ∗ Area	−.4029**	.0968
	(.1944)	(.1954)
BusRate	.2055**	.1693*
	(.1009)	(.0980)
Council Tax	1.3153*	−.7576
	(.6933)	(.5914)
Unemployment	−1.1163	.0270
	(2.5784)	(2.4320)
Youth	.6363	−.8777
	(2.4344)	(2.3193)
Pension	−3.4895	−5.6388*
	(3.3107)	(3.1058)
Wage	.1183	−.1740
	(.1833)	(.1788)
Rival Outlets in Neighboring Markets	−.02730	.0470
	(.0544)	(.0499)
Own Outlets in Neighboring Markets	−.0966***	.0215
	(.0168)	(.0125)
London	.0654	−.3932
	(.2738)	(.2453)
Number of observations	2,260	2,260
Log-likelihood	−428.6151	-516.5655
T1	283.0000 (28)	237.6239 (29)
T2	62.4884 (9)	72.7300 (11)
(pseudo) R^2	.2491	.1874

Notes: Numbers given are coefficient and standard error (in parentheses). Estimations include year dummies (some significant in the case of BK) and dummies for missing data cases described in the text.
***, **, and * denote significance at the 1%, 5%, and 10% levels.
T1 = LR-test of joint significance of RHS variables (d.f.).
T2 = LR-test of joint significant of market structure variables (d.f.).
Pseudo-R^2 for probit is calculated as $1-(L_1/L_0)$, as recommended by Cameron and Windmeijer (1997).

have a significant impact upon the outcome, were jointly insignificant, and the results otherwise were close to those reported. We also estimated restricted models to see at what level the controls for unobservables became significant. It transpired that as long as we had *Population* (and even only *Population*) as an explanatory variable, the random effects (fixed effects in LPM) were insignificant and small. Our final test relating to unobservables included additional data. We collected auxiliary data on a random sample of 30 restaurant chains, with the idea that in equilibrium, a greater taste for eating out translates into the market providing more restaurants.[18] These we aggregated into a single count variable. The idea is that if the unobservables are related to "taste for eating out," the number of outlets of these chains provides a direct measure of that. We used two forms of the variable: one included and the other excluded roadside chains (recall that we excluded roadside outlets for BK and McD). Including these variables in various forms never produced significant coefficients, and had no effect on our market structure results.

[18] The construction of this random sample is described in the Data Appendix, available from the authors on request.

TABLE 4 Marginal Effects of Market Structure Indicators

Market Structure Dummies	BK	McD
$M1, B0$	.1089***	.0413***
	(.0315)	(.0150)
$M1, B1$	.0185	.0589**
	(.218)	(.0247)
$M0, B1$	.0528	.0345
	(.0404)	(.0294)
$M2, B0$	.1834***	.1448***
	(.0553)	(.0428)
$M2, B1$	.0442	.1759***
	(.0313)	(.0524)
$M0, B2$	—	.1585**
		(.0847)
$M1, B2$	—	.1233
		(.0798)
$M2, B2$	−.0074	.2341**
	(.0299)	(.1120)
$M3, B0$	.2011***	−.0037
	(.0935)	(.0066)
$M3, B <$	.0291	.2584***
	(.0281)	(.0693)
$M <, B3$	−.0102	
	(.0316)	—
ρ^a		
Number of observations	2,260	2,260

Notes: $M3, B <$ means (number of McD outlets > 2, and number of BK outlets $<$ number of McD outlets). $M <, B3$ is defined similarly. Numbers given are marginal effect and standard error (in parentheses).
***, **, and * denote significance at the 1%, 5%, and 10% levels. Models estimated using a random-effects probit estimator.
[a] The ratio between the individual (random-effect) and common error terms' variance was $< .001$, and the random effect was therefore excluded.

We tested the robustness of our market structure results further by first taking a second-order polynomial of the market characteristics vector used in the base specification, the idea being that this allows us to capture possible nonlinearities that may bias our market structure coefficients. Second, we excluded all those market characteristics that carried insignificant coefficients in the base specification. The results on our market structure variables were practically identical to those we report.

Then there is the issue of the estimation sample. We experimented with leaving markets out of the sample by deleting first observations (markets) with a population less than the median; second, markets with a geographic area above the median; third, markets with a population density below the median; and fourth, markets with population above 1.4 times the median.[19] The first directly addresses the question that some markets are not viable in terms of the number of potential customers. The second and third address the potential problem of some of our markets being too large to be considered single markets (rather than a collection of markets) by the firms; and the last addresses the issue of people not being willing to travel far for fast food. Our results survive these tests.

We further experimented with leaving out London; with including growth rates of market characteristics; and with adding the lagged entry decision of the rival into the estimating equation.

[19] This is the lowest threshold that allowed us to use the same vector of market structure indicators as in the base specifications.

We added region-specific time dummies using 11 regions.[20] We also estimated the model excluding the 1995 data to control for the expiration of the contract between Grand Met (BK) and Wimpy; we used different distributional assumptions and estimated a bivariate probit to control for the possible simultaneity of the entry decisions. Our results were robust to all these experiments.

To further study the robustness of our results, we resorted to within-market micro-evidence.[21] We examined specific locations of outlets for all those markets that fulfilled the following criteria: both players are present in the market for at least a part of the 1991–1995 period; clear date order in which players entered; and at least three outlets in total by the end of the 1995. 57 of our districts satisfied these criteria. The results are clear cut. We are able strongly to reject the null hypothesis that distances between the outlets are equal in favor of the alternative that the follower outlet is closer to the initial outlet of the leader than are any subsequent leader outlets. Moreover, across our 57-observation sample, the median of the minimum distance between the qualifying outlet pairs is only 253 meters, clear evidence of a tendency toward closeness and circumstantial evidence in favor of learning from the other player.

Finally, 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, strong qualitative and quantitative reasons why a calendar year is a natural choice.[22]

5. The structural model and its estimation

■ **Functional forms and unobserved heterogeneity.** We operationalize the structural model by following Bresnahan and Reiss (1991) and assuming that the reduced-form profits gross of entry cost can be expressed as the product of a market-size function $S(\cdot)$ and a profits-per-expected-customer function $V(\cdot)$. Specifically, we model learning as learning of market size, and therefore we include the number of rival outlets at the end of the previous period into $S(\cdot)$. We then include the number of outlets at the end of the *current* period into $V(\cdot)$. The idea is that learning can take place only through observing the profitability of existing outlets, while the number of outlets at the end of the current period affects profits per customer. Note that identification of the learning effect relies on two distinct sources. The first relates to the use of the number of rival outlets at the beginning of the period to identify learning, and the number of rival outlets at the end of the period to identify the effects of rival presence on variable profits. The second relates to functional-form assumptions of the market-size and variable-profit functions. Identification through functional form alone is usually viewed with suspicion; our approach of strengthening this source of identification with another may also be criticized.

The existence of markets with no existing own outlets and markets with a positive number of existing own outlets allows us to identify all the parameters in $S(\cdot)$, $V(\cdot)$, and $F(\cdot)$ given our functional-form assumptions, as the entry rules differ between these two settings (see equations (3) and (4) in Section 2). Not knowing the size of the market means that the realized profits may be lower than expected. This could lead to exit (something we observe very little of in the data). Notice, however, that as long as (expected discounted) profits ($S(\cdot)V(\cdot)$) are nonnegative, remaining is more profitable than exit.

Regarding the error structure, we face the question of how to control for potential unobserved heterogeneity. The standard solution would be to add it linearly, implying that unobserved heterogeneity is due to unobserved between-market differences in fixed costs of entry. Although such differences may exist, a more plausible assumption is that our measure of market size does not capture all permanent differences between markets. Under this specification we model expected

[20] These regions are North, Yorkshire and Humberside, East Midlands, East Anglia, South East, South West, West Midlands, North West, Wales, Scotland, and Greater London.

[21] We are grateful to an anonymous referee for setting us off on the track reported briefly here.

[22] Both firms are publicly traded companies, and necessarily publish annual reports. They both also announce annual plans for new outlet openings. Using data on the within-year timing of McD's outlet openings from 1980 onward, it is clear that most open toward the end of a calendar year. On average, over 30% of all outlets open in December; 56% open in the 4th quarter; and only 5.4% open in the 1st quarter. Thus the calendar year appears to be the planning period for these firms.

market size as

$$S_{ijt}(\cdot) = Population_{jt} + \beta_{i_1} Youth_{jt} + \beta_{i_2} Pension_{jt} + \theta_{iS_1} Own_{jt-1} + \theta_{iS_2} Rival_{jt-1} + \theta_{iS_3} OwnNB_{jt} + \theta_{iS_4} RivalNB_{jt} + \rho_i \eta_j. \tag{7}$$

In (7), *Own* and *Rival* are the numbers of existing outlets (at the end of the previous period) in the district, ρ_i determines the variance share of the random effect, η_j is the market-specific time-invariant error term, and β_i, θ_{S_i}, and ρ_i are firm-specific (vectors of) parameters to be estimated. In standard fashion, we assume that η_j is independently and identically normally distributed with zero mean, that $\mathrm{cov}(\eta_j, \varepsilon_{ijt}) = 0$, and that $\sigma_\varepsilon^2 \equiv 1$.

Following Bresnahan and Reiss (1991), we measure market size by population,[23] but because different age groups display different tastes for eating hamburgers, we add age group controls into $S(\cdot)$. We include own and rival outlets in neighboring markets (measured at the end of the previous period) in $S(\cdot)$, 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 $S(\cdot)$ is normalized to one following Bresnahan and Reiss (1991). The coefficients of the $S(\cdot)$ variables can then be interpreted as increases or decreases in expected market size, measured in population equivalents.

We specify variable profits per customer as

$$V_{ijt}(\cdot) = \gamma_{i_1} Area_{jt} + \gamma_{i_2} Wage_{jt} + \theta_{iV_1} Own_{jt} + \theta_{iV_2} Rival_{jt} + \theta_{iV_3} Own_{jt} * Rival_{jt} + \theta_{iV_4} OwnNB_{jt} + \theta_{iV_5} RivalNB_{jt}. \tag{8}$$

In (8), γ_i and θ_{V_i} are firm-specific parameter vectors to be estimated. Incorporating the set of neighbor variables into $V(\cdot)$ 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 markets. If these operations are characterized by economies of scale, we would expect θ_{iV_4} to obtain a positive value. Insofar as the rival's operations have this characteristic, the number of rival outlets in neighboring markets affects the rival's marginal costs in market j, and therefore its market position. If so, we would expect θ_{iV_5} 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 that consumers derive from patronizing an outlet. The latter may both shift out the budget constraint and lead to higher wage costs. Including own and rival outlets into $V(\cdot)$ needs no explanation.

Finally, we assume that the fixed costs of entry are given by

$$F_{ijt}(\cdot) = \delta_{i_0} + \boldsymbol{\delta}_{it} \boldsymbol{t} + \varepsilon_{ijt}. \tag{9}$$

In (9), $\boldsymbol{t}$ is a vector of indicator variables for years 1992–1995. Including the time dummies into fixed costs instead of $S(\ )$ or $V(\ )$ is the simplest, but admittedly ad hoc, way to include them. We assume for identification that ε_{ijt} is distributed $\Phi(0, 1)$.

For markets without existing own outlets, the entry rule takes the following form:

$$S(\cdot)[\gamma_{i_1} Area_{jt} + \gamma_{i_2} Wage_{jt} + \theta_{iV_1} + \theta_{iV_2} Rival_{jt} + \theta_{iV_3} Rival_{jt} + \theta_{iV_4} OwnNB_{jt} + \theta_{iV_5} RivalNB_{jt}] - (\delta_{i_0} + \boldsymbol{\delta}_{it} \boldsymbol{t} + \varepsilon_{ijt}) > 0.$$

This allows us to identify all parameters in $S(\cdot)$, all the market characteristic parameters in $V(\cdot)$ (the γ_{ij}'s), the neighbor parameters, and the own outlet coefficient in $V(\cdot)$. Also, we can identify the entry cost parameters $F(\cdot)$. We cannot separately identify the rival and rival-own-outlet variables' coefficients (θ_{iV_2} and θ_{iV_3}).

[23] We experimented with different normalizations (*BusRate*, *Area*). The results were close to those reported.

The entry decision rule in markets with existing own outlets takes the following form:

$$S(\cdot)(\theta_{iV_1} + \theta_{iV_3} Rival_{jt}) - (\delta_{i_0} + \boldsymbol{\delta}_{it}\boldsymbol{t} + \varepsilon_{ijt}) > 0.$$

This allows us to identify all coefficients in $S(\cdot)$ and $F(\cdot)$, and θ_{iV_1} and θ_{iV_3} in $V(\cdot)$, i.e., the own outlet and the own-rival outlet variables' coefficients. As we estimate the entry decisions into these two types of markets jointly, we can identify the linear rival outlet coefficient in $V(\cdot)$ by combining the information in the above equations. Our assumption that zero own outlets yields zero profits underlies this identification argument.

□ **Estimation of the random-effects models, and the leader equation.** The introduction of random effects presents two difficulties: first, as the error component is placed in $S(\cdot)$, it is multiplied by $V(\cdot)$, 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 (see 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, 2000, for a recent exposition[24]). We opted for MSL instead of simulated method of moments (MSM) or some other simulation estimator for reasons explained by Hajivassiliou (2000) and endorsed by Hyslop (1999). The distribution of our dependent variable is skewed (see Section 3), and MSL has proved more robust than other simulation-based estimation methods in such circumstances.

Given that the time-invariant component of the error term is in $S(\cdot)$, leading to a model with random coefficients, we operationalize the simulation estimator by taking 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)[25] 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 antithetic variable techniques.[26] We performed a small-scale Monte Carlo simulation study (described in the Simulation Appendix, which is available upon request) and confirmed that our estimator performs well with the assumed error structure. 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. Therefore, we also tested the robustness of our results for the standard assumption of the random effect, namely that it is additively separable (and thus, in our specification, part of the fixed costs of entry).[27] 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 spurious state-dependence issue 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 plausible that the number of existing outlets, both own and rival, is correlated with unobservables. 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 structural estimations by projecting the market-

[24] 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.

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

[26] Antithetics is a powerful variance reduction method, e.g., Stern (1997), that greatly reduces the simulation error.

[27] We find this latter interpretation less plausible. Also, because 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 1 is due to unobservables.

specific time-invariant unobservables separately onto both own and rival existing outlets, and we denote these firm-specific projection coefficients by μ_{iOWN} and μ_{iRIVAL}. In other words, if there were spurious state dependence, the number of both existing own and existing rival outlets and the unobservables would correlate positively. By projecting the market-specific error term onto existing outlets, we remove this effect from the coefficients of interest. The (follower) simulated log-likelihood function for firm i is then of form

$$\log L_i = \sum_{ijt}\left[y_{ijt}\ln\frac{1}{R}\sum_{r=1}^{r=R}\Phi\Big[S(\cdot,\rho_i\eta_{jr})V(\cdot) - f(\cdot) + \eta_{jr}(\mu_{iRIVAL}Rival_{jt} + \mu_{iOWN}Own_{jt})\Big]\right.$$
$$+ (1-y_{ijt})\ln\left[1 - \frac{1}{R}\sum_{r=1}^{r=R}\Phi\Big[S(\cdot,\rho_i\eta_{jr})V(\cdot) - f(\cdot) + \eta_{jr}(\mu_{iRIVAL}Rival_{jt}\right.$$
$$\left.\left. + \mu_{iOWN}Own_{jt})\Big]\right]\right], \qquad (10)$$

where y_{ijt} is an indicator variable for entry by firm i into market j in period t, and η_{jr} is the (rth) simulated error term specific to market j.

Regarding the endogeneity 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 $\hat{\Pi}^{BK}_{McD} = \hat{\Pi}^{BK}(\cdot, Rival_{jt}+1)$ and $\hat{\Pi}^{BK}_{noMcD} = \hat{\Pi}^{BK}(\cdot, Rival_{jt})$. 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 the beginning-of-period value. Note our assumption that a new McD outlet does not influence BK's estimate of market size ($S(\cdot)$), only its variable profits ($V(\cdot)$). 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 $1(\cdot)$ is an indicator function taking the value one if the statement in parenthesis is true and 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.

□ **Follower (BK) results.** Before turning to the results, we point out that in all our estimations, the coefficient of own outlets in $S(\cdot)$ was either insignificant or carried the wrong (negative) sign. We interpreted this as a problem of identification (relative to $V(\cdot)$) and, therefore, excluded the variable Own_{jt} from $S(\cdot)$ in all the structural-form estimations. The results are reported in Table 5. We have estimated the model under the three alternative error structures outlined above, but for brevity we report only the standard probit results.

Looking first at BK, we find some indication that an increase in the proportion of pensioners or young people leads to a reduction in estimated market size. More important, rival outlets have a large significant effect on estimated market size: one rival outlet leads BK to increase its estimate of market size by 18,000 people. Also, the numbers of own outlets in the neighboring districts carry significant coefficients in $S(\cdot)$.

Area has no effect on variable profits, but *Wage* increases them, presumably because it is proxying income. The number of own outlets increases variable profits, whereas $V(\ )$ is 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 (i.e., number of own and rival outlets in neighboring markets) carries a significant coefficient.

We estimated the model with the more complicated error structures outlined in the previous

TABLE 5 Structural Estimations

Function/Variable	(1) BK Standard Probit	(4) McD Standard Probit
Market size		
β_{i_1}/Youth	$-.2848^{***}$	$-.2282^{**}$
	(.0884)	(.1052)
β_{i_2}/Pension	$-.4308^{***}$	$-.4205^{***}$
	(.1019)	(.1113)
θ_{iS_2}/Rival Outlets	$.1820^{**}$	$.3203^{**}$
	(.0795)	(.1391)
θ_{iS_3}/Own Outlets in Neighboring Markets	$.1139^{***}$	$-.0164$
	(.0409)	(.0162)
θ_{iS_4}/Rival Outlets in Neighboring Markets	$-.0503$	.0012
	(.0173)	(.0077)
Variable profits		
γ_{i_1}/Area	$-.4740$	$-.5269$
	(.3251)	(.7069)
γ_{i_2}/Wage	$.0474^{***}$	.0200
	(.0169)	(.0203)
θ_{iV_1}/Own Outlets	1.3980^{***}	1.8616^{***}
	(.4014)	(.6306)
θ_{iV_2}/Rival Outlets	.1360	.2526
	(.1711)	(.3124)
θ_{iV_3}/Own Outlets $*$ Rival Outlets	$-.0590^{***}$	$-.3257^{***}$
	(.0238)	(.1219)
θ_{iV_4}/Own Outlets in Neighboring Markets	$-.1091$	$-.3291$
	(.0902)	(.2431)
θ_{iV_5}/Rival Outlets in Neighboring Markets	$-.0381$	$.2653^{*}$
	(.0485)	(.1538)
Fixed entry costs		
δ_{i0}	-2.4134^{***}	-2.4495^{***}
	(.1875)	(.1832)
δ_{i92}	$-.5820^{***}$	$-.2429$
	(.1729)	(.1776)
δ_{i93}	$-.3160^{*}$	$-.0273$
	(.1685)	(.1637)
δ_{i94}	$-.1497$	.1344
	(.1513)	(.1638)
δ_{i95}	$-.0079$	$-.1406$
	(.1550)	(.1731)
Number of observations	2260	2260
Log-likelihood	-422.2677	-544.5235
Estimation method	ML	MSL
Number of simulations	—	40

Notes: The simulation estimator uses antithetics. Numbers given are coefficient and standard error (in parentheses).
***, **, and * denote significance at the 1%, 5%, and 10% levels.

section. It turned out while the rival outlets coefficient in $S(\cdot)$ became insignificant, the coefficient of the random effect was always highly insignificant, and we could never reject the null of a standard probit error structure. Our results were robust to the inclusion of the number of outlets of other restaurant chains or *BusRate* into $S(\cdot)$. Finally, we explore the learning effect in more detail by allowing the coefficient of rival outlets in $S(\cdot)$ to take different values in markets with own, and no own, existing outlets. The (unreported) results show that BK learns from McD only if it has no own existing outlets in the market. Calculating the marginal effects of market structure on entry probabilities in line with those reported for the reduced-form results in Table 4 showed that they were highly significant and qualitatively similar to, although smaller in absolute size than, the reduced-form marginal effects.

□ **Leader (McD) results** All McD results are produced using MSL. As with BK, we estimate the model using three different error structures. We find that the proportions of pensioners and of under-16's have a negative impact on McD's estimated market size. Numbers of outlets 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 (.32) and highly significant (p-value .021). This is evidence that McD uses BK outlets to update its beliefs on market size.

Considering the variable-profit function, we find that *Area* and *Wage* have no statistically significant impact. 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, but McD profits are more sensitive to competition than BK's. The effect of competition comes through the interaction term, as the *Rival* outlet coefficients are insignificant for both firms.

One advantage of the structural estimates is that they reveal the various forces at work more clearly than the reduced form. For example, if McD (BK) opens a second outlet in a market with one rival outlet, there are two effects on its variable profits. The first comes from the *Own* outlet variable, increasing profits by 1.86 (1.40). The second is the competition effect coming from the interaction term. In our example, competition from the one BK (McD) outlet would lower McD (BK) profits by .32 (.06). Thus the effect of a second outlet on variable profits per customer for McD (BK) would be $1.86 - .32 = 1.54$ (1.33).

The market-definition controls are insignificant. Estimated fixed costs do not vary significantly over time, and they are similar in size to BK's, except in 1992. The pattern of results from the specifications with more-general error structures was similar to that for BK: we found no evidence for unobserved heterogeneity. Our experiments with including the number of other restaurant outlets, or *BusRate,* produced insignificant coefficients for those variables, and rival outlets' effect on $S(\cdot)$ was not affected. When we allowed the effect of rival outlets in $S(\cdot)$ to differ with (not) having own outlets, we found that whether or not McD has own outlets makes little difference. As with BK, the market structure marginal effects were highly significant and qualitatively in line with those from the reduced-form results.

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. All this suggests that the firms are offering differentiated products, implying that it may be problematic to impose symmetry upon firms' profit functions even if the firms seem similar upon first inspection.

6. Conclusions

■ The objective of this article was to shed light on entry in markets with multiplant firms (chain stores). The particular questions explored were the identity of the entrant, and whether existing presence deters entry generally. In contrast with the recent empirical entry literature, we estimate firm-specific equations. At least with our data, we find that firms react differently to market characteristics and hence that differentiating between firms in modelling is an important flexibility. 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 article. 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 to greater ability to exploit economies of scale, we cannot tell.

Our most novel finding is that both firms use rival presence to revise upward their expectations of market size. Thus rival presence has two quite different effects, one positive and one negative. A large set of tests showed that our main result is robust. These, the various econometric controls that we employed, and the fact that own entry is not positively affected by own presence but only by rival presence suggest to us that unobserved market characteristics are unlikely to explain this result. However, one might still object to our interpretation of the result by questioning our market definitions or our controls for market characteristics. Moreover, a dynamic framework may well provide additional insights, enabling sharper prediction of the timing of entry, for example.

Returning to the question posed in our title, the "beef" is most likely in learning. The two firms we study are large, professionally managed organizations, both of which have honed 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 known worldwide. Nevertheless, our results are difficult to explain within the theoretical framework of Shaked and Sutton (1990) that encompasses much of the theoretical literature on entry. They are not what would be expected from an entry-prevention strategy. Instead, they indicate that there are positive spillovers to both firms from the presence of the rival in a given market.

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