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ABSTRACT

Retail Chain Expansion: The Early Years of McDonalds in Great Britain*

Understanding the development of chainstores is important given the large GDP share of services and the continuing importance of chains in bringing these services to market. Service chains provide a puzzle because they take a long time to develop even when there are obvious expansion opportunities. We study the spread of McDonalds in Britain. We find cannibalization on the demand side and economies of density both within and between markets on the cost side, and evidence of learning by doing at the firm level. Within-period diseconomies of scale at the firm level help explain the lengthy opening pattern.

JEL Classification: L10, L22 and L81
Keywords: cost of entry, diffusion, economies of density, economies of scale, entry and expansion

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1. Introduction

The motivation of this paper builds on the following two observations: First, the retail sector is of major importance in modern economies, providing the avenue through which new goods and services are brought to consumers.[1] Second, the internet notwithstanding, the majority of goods and services are still delivered at a physical location. Taken together, these observations suggest that it is important to understand the dynamics of the retail sector, i.e., how service sector firms expand their store network. This is the objective of this paper. We hope to achieve it by studying a particular firm, McDonald's (McD), in a particular market, Great Britain. This case is of interest because it represents a wider phenomenon, and because, due to its simplicity, it allows a more complete analysis of the firm's underlying cost structure than has been possible so far.

There are striking regularities in the expansion of (successful) retail firms such as Walmart, McD or indeed IKEA: After starting from one location, they expand organically. Expansion takes time: They do not open immediately even in markets that must have seemed profitable to enter right away. In the case we study, it took McD, a very large firm with lots of experience in opening outlets by the time it established itself in the UK in 1974, 7 years to reach the 2nd largest city in the UK, only a little over 100 miles from its first store. Service firms seem also to expand round their existing outlets. Finally, the rate of expansion increases over time to subside when saturation is approached. A model of service firm expansion needs to be able to explain these regularities.[2] These features, at least in our data, are not

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[1] To give one measure, distribution and retailing is a larger sector than manufacturing in the UK by value added.

[2] In addition, exit is very rare. Thus we cannot examine its determinants, but it indicates the soundness of the expansion pattern.

explainable by demand side dynamics and our main focus is on understanding the cost structure in some depth.

We model McD, in the years up until 1990, as a single agent developing its network without significant competition. Seen from a position of hindsight, it is difficult to appreciate the sense of novelty created by early experiences of McD in the UK. Counter service take-away food was well known in the UK through fish and chips, although restricted to particular times of day and eaten out of newspaper in the main. Burger restaurants were also known through the Wimpy brand, although here the focus was very much on table rather than counter service.[3] McD brought these elements together in an environment that was significantly swifter, smarter, cleaner and more controlled than the alternatives. Essentially, until Burger King took over some Wimpy restaurants and began redeveloping them as counter service in 1990, McD had the field to itself and a market share of around 80%. A listing of significant events is given in Table 1.

[TABLE 1 HERE]

Our structural dynamic model of firm expansion gives the firm in each period the option of opening an outlet in each of the several markets. These markets are related geographically to each other. The firm faces both a local cost of entry, and a firm level cost of entry. The former is affected by local conditions, such as the existing number of outlets in the particular market and (potentially at least) in the neighboring markets. These economies of density (Holmes 2011), or local economies of scale, explain the expansion around existing outlets. The firm level entry cost is affected by the number of outlets opened in a given period, and by the total number of outlets opened earlier. At the firm level, there may be diseconomies of scale in opening too

[3] The Wimpy chain had also developed a somewhat negative image.

many outlets at once, explaining the slow diffusion so often observed. These are however moderated by what one might call learning by doing: We allow the number of previously opened outlets to affect firm level costs (as with aircraft - see e.g. Benkard, 2000). These, in turn, explain the increasing pace of diffusion over time. Finally, crowding the space offers a natural explanation for the slowing of the diffusion process. It may also be that the learning by doing subsides after some number of outlets has been opened.

We find that there are no local economies of scale on the demand side: On the contrary, the n^{th} outlet obtains only 68% of the sales of the $n\text{-}1^{st}$. At the same time, the raw data reveals that the ratio of population to outlets is decreasing in the number of outlets in a market. This fact strongly suggests local cost side economies of density. This is what we find, both within a market, and between neighboring markets. Experience, gained and measured through the cumulative number of opened outlets, pushes firm level costs down, explaining for its part the increasing pace of entry. However our most novel finding is that costs of opening outlets are increasing in the number of outlets opened in a given period, giving the firm an incentive to spread entry over time. Finally, we estimate the (average) price-cost margin of McD to be 30%.

In estimating the model we build on the recent advances in econometric methods developed for dynamic structural models (Aguirregabiria and Mira 2002, 2007, Berry, Ostrovsky and Pakes 2007, Pesendorfer and Schmidt-Dengler 2008, and Bajari, Benkard and Levin 2007, henceforth BBL). Our choice of estimation method is dictated by our need to allow a large state space, and we therefore use the estimator developed by BBL (which is equally suited for single agent decision problems, although their application is to dynamic games). Our estimation approach follows an insight of Bresnahan and Reiss (1994) and Berry and Waldfogel (1999):[4] We use data on sales to estimate parameters governing profits gross of fixed costs, and data on entry decisions to estimate the cost side parameters. Our novelty on the sales side is to aggregate the sales in those markets where McD is present to yield an expression of firm level sales, and to estimate that using the available firm and market level data.

The phenomenon we study has attracted interest for a long time, and especially recently. Holmes (2011) studies the diffusion of Walmart in the US in a very elegant paper on which we build. Holmes states the decision problem of Walmart concisely: 1. How many new stores (and of which type) to open (this year)? 2. Where to put these stores? 3. How many new distribution centers to open? 4. Where to put these? Given the complexity of Walmart's decision problem, Holmes concentrates on modeling question number 2, conditioning on the other three. Here we benefit from the fact that McD runs a much simpler operation than Walmart: Its product line is much smaller and more uniform; its store size does not vary greatly and we can therefore abstract from that variation; and given that McD had only one distribution center during our observation period, we do not need to model questions 3 and 4 at all. Similar to Walmart, the opening decisions are done centrally in McD (whether the particular outlet will be managed, as most are in our period, or franchised).[5] Using Holmes' description of Walmart's decision problem, McD faces only questions 1 and 2, and we are able to address both simultaneously.

In another interesting recent paper, Jia (2008) models the effects of competition on the location of stores. She studies the competition between Walmart, Kmart, and local producers. She elegantly solves the computational complexities that arise from having

[4] See Berry and Reiss (2007) and Berry and Tamer (2007) for surveys of the literature on empirical research on static entry models.

[5] This is apparent from our inspection of McD franchise agreements, held on file at the UK's Office of Fair Trading.

to model a game. We avoid these complexities by concentrating on McD's first 15 years (1974 – 1990) in the UK when it was the only significant firm offering American style burgers through a chain of outlets. Nishida (2010) studies a problem that shares commonalities with Jia's. In common with us, he allows for multiple outlets per firm, and uses revenue data, but focuses on a cross-sectional sample of outlets.

Given their prominence in retailing, McD and its rivals have been the subject of previous research in industrial organization. Toivanen and Waterson (2005) study the interdependence of McD and Burger King entry decisions using data from the same markets as the current paper, but from a later period (1991-1995). They find that rival presence increases the probability of a firm entering a market – a result that is robust to unobserved market-specific heterogeneity. Aguirregabiria and Magesan (2011) study firms' beliefs using the Toivanen-Waterson data. They confirm the Toivanen-Waterson results and find that BK underestimated McD's entry probability in markets where a McD already existed. Yang (2010) studies the Canadian fast food industry and presents an interesting methodology to separately identify demand spillovers from strategic learning. Kosová and Lafontaine (2010) use data on a large number of franchise chains in retail and service industries to study growth and survival. They find that age and size affect growth and survival even when they control for chain characteristics and unobserved efficiency at the chain level. In a departure from these papers and most of the related literature (for a recent exception, see Benkard, Bodoh-Creed and Lazarev, 2010, on airline mergers), we do not assume that entry by the same firm in different markets is independent of each other; rather, the interdependence of these decisions is at the core of our approach.

Other scholars have studied non-entry aspects of McD operations: Thomadsen (2005) studies the pricing of McD and BK and conducts counterfactual merger experiments. Kalnins (2004) studies the pricing of hamburgers using spatial econometrics methods. He finds that the neighboring outlets of different chains are not close substitutes. Kalnins and Lafontaine (2004) study the franchising decisions in the Texas fast-food industry. They find that the probability that the ownership of a new outlet is given to a particular franchisee is decreasing in the distance between the new outlet and the nearest outlet the franchisee is already operating.

The rest of the paper proceeds as follows: In the next section, we describe McD's diffusion process in the UK, the data we have, and justify our assumption of assuming no strategic competitors. In section 3 we build the model and explain how we estimate it. Section 4 is devoted to reporting our parameter estimates, and section 5 to reporting our counterfactual analysis. Section 6 concludes. We leave open such policy questions as whether the planning system has much influence on the pace of expansion.

2. The Diffusion Process and the Data

2.1. The Diffusion Process

Whilst clearly smaller than Walmart, McDonalds is the world's largest food services company by revenue (Fortune, 2008) with, according to its corporate website, "more than 30,000 local restaurants serving 52 million people in more than 100 countries each day". The UK currently has over 1000 restaurants. Store openings in the UK are planned centrally and McD's UK website states: "Opening the right type of restaurant in the right location is therefore vital to the Company's continuing success".

We examine the diffusion of McDonalds in Great Britain[6] (GB) starting from its commencement of operations in 1974 until 1990. We conclude our investigation in 1990 because from 1991 onwards, McDonalds is best described as being in duopolistic competition with Burger King, adding a discrete step to the degree of complexity of the analysis. Until 1990, McDonalds was essentially the only significant supplier of fast food burgers and we treat it as a monopolist in this market.[7] As we document below, the impact of McDonalds in GB has parallels with the spread of Walmart in the US. Both expand through outlets in new centers as well as outlets in markets with existing outlets. During this period, McDonalds was essentially a town-centre chain, occupying (after refitting) an established store in an established shopping location. It did not start operating drive-through outlets until 1986, and drive-through only outlets until 1995, also the date when the first motorway-service outlet was opened.

We follow Toivanen and Waterson (2005) and take as our geographical market the Local Authority District (LAD). LADs are the smallest unit of local government in Great Britain and consist of a city, a town with some hinterland, or a largely rural area. We take advantage of the considerable heterogeneity across the 455 LADs in our population which is described in more detail in section 2.2.

Figure 1 shows McD's expansion by plotting the (logged) number of outlets against calendar time. From one outlet in 1974 the firm expands to 381 in 1990 (and over a thousand by 1999). The growth rate is clearly increasing (at a decreasing rate) during our observation period. Figure 2 plots McD's revenue against expenditure on fast food consumption, as described in section 2.2 below. This is obtained by

[6] We do not include Northern Ireland.

[7] We would argue that the only significant pre-existing chain, Wimpy, was a somewhat lacklustre and indirect competitor for reasons set out in Toivanen and Waterson (2005). Toivanen and Waterson (2005) also discuss the reasons why Burger King emerged as a strategic competitor in 1991. The main reason was a merger and reorganization and re-badging of outlets.

multiplying population covered by McD[8] (from Regional Trends) by a proxy for per capita fast food expenditure. Figure 2 illustrates how closely linked McD sales are to the population (weighed by expenditure) that has access to McD outlets. The correlation between sales and population (in the markets with at least one McD outlet) is 0.98, and that between sales and the number of outlets 0.99, both measured using data from the period 1975 (first year of positive sales data) to 1990.

[FIGURES 1 AND 2 HERE]

Figure 3 looks at geographical coverage by conditioning on the number of outlets existing by the end of the year. Very clearly, by 1990 there are very few markets with 3 or more outlets, while the number of markets (LADs) with one or two outlets has grown steadily. By end of 1990, 239 out of 455 markets have at least one outlet, 74 at least two, and 31 three or more outlets.

[FIGURES 3 AND 4 HERE]

Figure 4 shows the amount of population per outlet in 1990, conditioning on the number of outlets in a given market. It is interesting to note that the amount is decreasing in the number of outlets, with the exception of five-outlet locations which is affected by the small number of markets with five outlets (five in 1990). This pattern suggests some type of economies of scale, either on the demand and/or the cost side. Our estimation approach allows us to disentangle these.

Figure 5 illuminates the geographical and time dimensions of the entry process. It shows that part of Great Britain where entry had taken place. Outlets are circles, and different colors indicate the year of entry. The first outlets outside London were opened in 1979, to the Northwest and Southeast of the capital. Only as late as 1981 were outlets opened clearly away from London, and then simultaneously both in the

[8] I.e., the population in those markets where McD has at least one outlet.

Birmingham area (the 2nd largest city), Derby (a medium sized city by UK standards), and several places in the vicinity of London. The years 1982 – 1984 saw several outlets being opened in the Birmingham and Manchester areas, but also in a rather scattered manner round England (not yet Scotland and only one in Wales). It is notable that in addition to the major Scottish cities and the Welsh capital Cardiff, several major regional cities with populations of 300,000 or more, both in the South West (Bristol, Plymouth) and towards the North East (Leeds, Britain's third largest city, Sheffield, Bradford, and Newcastle upon Tyne) still had no McD outlets after 10 years of expansion.

[FIGURE 5 HERE]

The patterns displayed in Figure 5 suggest the existence of economies of density - witness the rapid expansion round Birmingham soon after the first outlet was opened there. Given that changes in local population were much smaller than the cross-sectional variation in population, the increasing pace of openings, also in places quite far from existing outlets, suggest a reduction in entry costs over time.

An issue that e.g. Holmes (2010) has to confront are Walmart's distribution centers. Luckily for us, things are straightforward in the case we study. During our observation period, McD had a single distributor (Goldenwest) based in outer north London, supplying almost all the stores' food, packaging and ancillary requirements from this single location (McDonalds, 1995).[9]

2.2. The Data

We have collected the data on McD entry timing and location from a spreadsheet provided by the firm itself (see Toivanen and Waterson 2005). To this we have

[9] Goldenwest opened a 2nd distribution center in 1991.

matched data on LADs from the UK's *Regional Studies* for population. This annual publication lists area, population numbers, demographics and a variety of other information. We also generate a matrix of "neighbors" to each LAD, being the set of LADs which share a non-trivial land boundary with the LAD. Per capita expenditure on "fast food" is proxied by expenditure on "other meat and meat products" plus "soft drinks", from the UK Food and Expenditure Survey for the relevant year. Table 2 presents descriptive statistics for the years 1975, 1980, 1985 and 1990.

[TABLE 2 HERE]

Table 2 provides more information on the expansion process of McD. Although sales[10] and the number of outlets are growing at an increasing pace, sales per unit population in the markets with at least one McD store does not exhibit a clear trend. At the end of 1990, almost 40 million people are within reach of a McD, and there is at least one outlet in 239 out of the 455 LADs included in our sample.[11]

[FIGURES 6 AND 7 HERE]

To illustrate the heterogeneity over LADs, we present in Figure 6 the distribution of LAD population in 1974 and 1990. The two distributions are remarkably similar. Indeed, the cross section variation in population is far greater than the time-series variation. The within-LAD correlation of populations in 1974 and 1990 is 0.99. Figure 7 displays the distribution of LAD specific population growth rates. It is quite concentrated. The mean (median) of the growth rate is 0.4% (0.4%) with a standard deviation of only 0.7. The maximum (minimum) growth rate is 5.3% (-1.9%) and the 99th (1st) percentile of the growth rate distribution is only 2.5% (-1.3%).

[10] We take the sales figures from McDonald's financial accounts, as lodged at Companies House. There are some minor discrepancies between these and the figures listed in McDonalds (2007). In years 1991 and beyond, the outlet numbers diverge slightly more, as a result of openings in Northern Ireland, Jersey, etc.

[11] We exclude the following four GB LADs, all sparsely-populated peripheral offshore island groups: Scilly Isles, Orkney, Shetland, Western Isles.

3. The Model and Estimation

3.1. The Bellman Equation

We want to model the following situation: Each period, after having observed period- and market-specific (i.i.d.) cost-of-entry shocks, McD has the possibility of opening an outlet in each market. McD maximizes expected discounted profits, and views the entry decision as irreversible.[12] The expected discounted profits of opening the n^{th} outlet in market *i* are $\pi_i(n_i)$. Notice that $\pi_i(n_i)$ is not the market-level profit function (gross of entry costs), but the expected discounted value of profits generated if the firm opens a new outlet in market *i*. The profits generated by previously opened outlets do not affect this period's entry decisions directly. The number of previously opened outlets may affect the entry decision indirectly in two ways: First, through cannibalization of sales, which we model through $\pi_i(n_i)$. Second, they may affect the entry decision through cost of entry, which we model next.

The cost of opening the outlet is decomposed into two: The first is a market-specific part that may depend on the number of existing outlets in market *i*, and in neighboring markets ($k(n_i - 1, nbor_i)$). The second is a firm-level effect, and the total cost of opening outlets is given by

$$K_{McDt} = K(\sum_i d_{it}, \sum_i \sum_{\tau=1}^{t-1} d_{iy\tau}) + \sum_i d_{it} k(n_{it} - 1, nbor_{it}),$$

where d_{it} is an indicator function taking the value 1 if entry in market *i* takes place in year *t*. The first part of the cost-of-entry function allows for a firm level effect. It is first of all a function of the number of outlets opened in this period. We allow it also to be a function of the total number of outlets opened in the past (*y* indexes time). We

[12] As noted above, exit is very rare and we therefore do not consider it.

assume that $K(\sum_i d_{it}, \sum_i \sum_l d_{iyt})$ is sufficiently convex in $\sum_i d_{it}$ to make K_{McDt} convex. Given the above, the value function can be written as

$$\text{(1)} \qquad \arg\max_{d_i} V = \sum_i d_i \pi(n_i) - \left[K(\sum_i d_i, \sum_i \sum_y d_{iy}) + \sum_i d_i k(n_{i,} - 1, nbor_i) \right] + \beta V',$$

where we have left implicit the conditioning on the information available at the beginning of the period.

Notice that the state space of our problem is unusually large (at least relative to existing research in industrial organization). The number of state variables is the number of market-specific state variables times the number of markets (455) plus the number of firm level state variables. This, together with the large amount of cross-sectional heterogeneity in market sizes, necessitates us using an estimation method that allows for a large state space.[13]

3.2. Estimation

We follow Bresnahan and Reiss (1994) and Berry and Waldfogel (1999) by first estimating a revenue equation (Nichida 2010 is a recent example), and then using these estimates in the estimation of the entry decisions. We depart from these papers in three respects: First, we only have access to firm level sales data - our sales data is not disaggregated to the level of individual markets. We therefore have to devise a way to utilize the firm level information on sales, number of outlets, and market characteristics. Second, we estimate a dynamic model of entry, taking into account that the firm may enter several markets simultaneously. Third, the dynamic nature of

[13] In particular, given the small amount of time variation in population relative to the variation across markets it would have been difficult to discretize population in a way that would not have eliminated (most of the) over time variation.

our model (coupled with no exit) means that we need to calculate expected discounted revenues.

The revenue equation. Since the sales data is annual, we have very few observations to work with. To take this into consideration, we model McD firm level sales in year t as follows:

(2) $$sales_t = \left[(\mu + \alpha expend_t)\right] \sum_{n=1}^{n_{\max}} \delta^{n-1} \sum_i d_{nit} \, pop_{it}$$

where $expend_t$ is a variable measuring the proxied share of total food expenditure spent on eating out and d_{nit} is an indicator for the n^{th} outlet existing in market i in year t. What equation (2) tells is that sales are a linear function of population, with the effect of a one person increase in population being $\left[(\mu + \alpha expend_t)\right]$ if there is one outlet in the market. The effect of a 2nd, 3rd, etc. outlet on sales is that of the 1st outlet, multiplied by a "discount" factor δ that measures by how much sales increase from introducing the n^{th} outlet relative to the increase obtained from introducing the $n\text{-}1^{st}$ outlet. δ is thus a measure of "cannibalization" of sales from existing outlets. Because of the limited amount of data, we restrict the cannibalization effect to be constant over the number of existing outlets.

To estimate (2), we aggregate (by year) the population in markets with at least n outlets (with n = 1, …, 7), and regress annual sales onto these seven variables using nonlinear least squares, yielding estimates of the reduced form demand parameters in (2). We identify the parameters through variation (over time) in the amount of population in markets with n outlets, and in the changes over time in $expend_t$. To minimize the impact of common trends, we estimate (2) using first-differenced data. We use the sales (revenue) equation in the estimation of entry decisions by constructing the expected discounted sales of opening the n^{th} outlet in market i in year t for each of our observations using the parameters from this revenue equation.

Calculation of expected discounted sales. To calculate expected discounted sales from entry into market i in year t (*Esales*), we use as inputs coefficients from two regressions, and (simulated) data. By plugging both the (simulated) population in year t and the (simulated) number of McD outlets in the market opened prior to year t into equation (2) we get the expected sales for year t. To get expected sales for years t+1, …, T, we need the expected population from year t+1 onwards. To obtain these, we use the coefficients from market-specific 1st order auto-regressions of log population. We discount the future sales by the same discount factor we use in the structural model.[14]

The entry equation. To estimate the entry equation, we utilize the estimator developed by BBL. For our purposes, its main advantage is that it allows for a rich state space. This we need for two reasons: First, as mentioned above, the large number of markets necessitates a large state space. Second, the heterogeneity of markets in terms of population and therefore expected discounted revenues means that discretizing the revenues would either not lead to a large reduction in the dimensions of the state space, or would lead to a situation where a large number of markets would have no variation in our key variable over time.

The BBL estimator (see also Hotz, Miller, Sanders and Smith 1994) is a two-stage estimator. In the 1st stage, we estimate a *policy function*

$$d_{it} = 1\left[f(Esales_{it}, n_{it-1}, nbor_{it}, \sum_{i=1}^{I}\sum_{k=1}^{t-1} d_{ik}, \nu_{it}) \geq 0 \right], \quad (3)$$

[14] This feature of our model results in an "extra" simulation round for each of the BBL simulation rounds, making our model slower to estimate than what would normally be the case. To prevent expected discounted sales from exploding, we cap the coefficients for those half a dozen markets with high coefficients of lagged (log) population.

where the dependent variable is an indicator of entry in year *t* into market *i*, and the explanatory variables are market- and year-specific state variables: expected discounted sales from opening a new outlet in market *i* (generated as explained above), the number of existing outlets in market *i*, the number of existing outlets in neighboring markets, and the stock of opened outlets by year *t-1*. Notice that we estimate the policy function at the market, not the firm level.[15]

Having estimated the policy function, in the 2nd stage we simulate the entry decisions using i) shocks generated using pseudorandom numbers and ii) the policy function. This way we can calculate the value function for given values of the parameters of the per-period profit function. We take advantage of the fact, stressed by BBL, that linearity and additive separability means that we need not calculate the value function separately for new values of the parameters. This speeds up the computation significantly. Linearity and additive separability arise naturally in our case, as the per-period profit function consists of the entry costs and the expected discounted revenues (profits) from entering the markets.

The second stage of BBL is the estimation of the structural parameters using i) the computed value function using the actual (optimal) policy, uncovered in the 1st stage, and ii) some alternative policy (policies) which, by revealed preference, must yield weakly lower values for the value function. We generate M alternative policies by varying the estimated policy function parameters. We obtain point estimates (following BBL) minimizing the following objective function:

$$(4) \qquad Q_n(\theta,\omega) = \frac{1}{n_I}\sum_{k=1}^{n_I}[\min\{\hat{V}(X_k,\theta,\omega) - \hat{V}^a(X_k,\theta,\omega),0\})^2$$

where the $\hat{V}$'s are simulated value functions of the actual and the alternative policies, X_k is the set of inequalities (between the value functions of the actual and alternative

[15] For a similar solution in an environment where a firm makes simultaneously entry (exit) decisions over multiple markets, see Benkard, Bodoh-Creed and Lazarev (2010).

policies) chosen by the researcher, θ is the vector of parameters to be estimated, and ω is the vector of 1st stage parameters.[16] We calculate standard errors using subsampling.[17]

4. Estimation Results

4.1. The Revenue Equation

We have estimated the revenue equation (2) using data from the period 1974 – 1990. Given the very small sample these results must be viewed with some caution. The fit of the model is surprisingly good (R^2 = 0.9). As reported in column (2) of Table 3, our estimate of μ is -1.22, that of α is 0.05, and that of δ is 0.68. The μ estimate is insignificant, that of α is significant at 10% level, and δ is significant at the 1% level. The interpretation of the first two is that a person spends $\left[(-1.22+0.05*expend_t)\right]$ pounds per year on McD products given one outlet in the market. Given a mean value for $expend_t$ of 54, this translates into sales of £9.10 per person per year in 1996 pounds. This would correspond roughly to each person buying 3-4 meals (hamburger, French fries, drink) per year. The estimate of δ means that revenues from the second (more generally, n^{th}) outlet are 68% of those of the first (n-1^{st}) outlet. We thus find evidence of quite substantial negative economies of density (or "cannibalization") on the demand side.

[TABLE 3 HERE]

[16] In our case, ω includes the parameters from the firm level sales estimation, the market-specific 1st order population autoregressions, and the policy function estimation.

[17] The alternative policies' policy function parameters are generated as $\theta+0.5\theta\varepsilon$, where ε is distributed N(0,1) and θ is the parameter vector of the actual policy function. We set M = 250, and use R = 100 simulations when calculating the point estimates. We follow BBL in using subsampling and fewer simulations in estimation of the standard errors. In choosing subsamples, we choose "blocks", i.e., we subsample markets, not individual observations. We set M_{ss} = 100 and R_{ss} = 30. We experimented with different subsample sizes, noticed no difference, and used subsamples of 1/3 of the estimation sample.

One should note that pairing the above results of negative economies of density on the demand side with Figure 4 in section 2 suggests that positive economies of density on the cost side must exist. Figure 4 shows that the population/outlet is decreasing in the number of outlets; the above result tells us that sales per outlet are decreasing in the number of outlets. The latter finding suggests that without significant economies of density on the cost side, we would expect to observe the opposite of what is reported in Figure 4, namely population per outlet increasing in the number of outlets.

To check the robustness of our revenue results that rest on using a very limited amount of data, we re-estimated the equation (2) using data until 1996. The cost of using the longer series is that McD is no longer the sole “strategic” player, since BK’s reorganization (see Toivanen and Waterson 2005) created a much stronger competitor than it was prior to 1990. The results are very close (column (4)), and the implied sales per person per year from the 1st outlet almost the same (£9.50). Estimating the equation in levels (column (3), using data for 1974 - 1996) yields also sales worth £9.50/person/year. It therefore seems that the results are reasonably robust.[18]

4.2. Policy Function Estimation

We estimate the policy function (3) assuming i.i.d. normally distributed shocks v_i. We include linear and squared terms for most variables, and also a cubic term for the cumulative number of outlets opened (measured in year t-1). We have experimented with different specifications of the policy function and our structural estimates are robust in this respect. We report the policy function results in Table 4.

[TABLE 4 HERE]

[18] Though we could increase the sample further in the time dimension, it would pose some problems as the fraction of drive-through outlets starts to strongly increase from mid-90s onwards, meaning that the population of a market is no longer a good measure of potential demand.

Our results show that (the natural log of) expected discounted sales (lnsales) increases the probability of entry as it should, but at a decreasing rate; that the number of existing outlets has a positive effect on the probability of entry;[19] and that the (weighted) number of outlets in neighboring districts increases the probability of entry (here, the 1st order term dominates the 2nd order term up to 4 outlets in neighboring districts). When comparing the coefficient to that on outlets in the same district one has to bear in mind that neighboring outlets have been divided by the geographic area of the district (the mean of the neighbor variable is 0.2). Finally, we find a nonlinear effect from the number of outlets already opened (Total # outlets opened to date), measured at the firm level. At the level of the policy function, the results are supportive of the effects outlined above, with the possible exception of the effect of outlets in neighboring districts.

4.3. Estimates of the Structural Parameters

We specify the per period profit function as

$$\Pi = (\sum_i d_i\{\beta_1 Esales_i - [\theta_0 + \theta_1 n_i + \theta_2 n_i^2 + \theta_3 nbor_i + \theta_4 total_i + \theta_5 total_i^2]\}) - [\theta_6 \sum_i d_i + \theta_7 (\sum_i d_i)^2\ ] \tag{5}$$

In equation (5), the first term is the expected discounted sales from opening (the n^{th} outlet) in market *i*; the terms within the first squared brackets measure the market entry costs; and the terms within the second squared brackets measure the firm level costs of entry. The first cost of entry - term is the fixed cost of opening an outlet; the second and third measure the impact of the number of (previously opened) outlets in market *i* on the cost of entry. The *nbor* variable is the number of outlets opened in

[19] We experimented with using sales and sales squared instead of logs. These obtained insignificant coefficients. The coefficients of the other variables maintained their signs and significance levels without large changes in size. We did not include the squared number of existing outlets as it obtained an insignificant coefficient.

previous periods in neighboring markets (weighed by area), and the *total* variable in turn measures the number of outlets opened to date across all markets. It captures learning by doing. The last two terms pick up the within-period (dis)economies of scale by adding the number of outlets opened in this period to the equation. As can be seen from equation (5), we allow for nonlinearities through second order terms for local (dis)economies of scale (number of outlets that already exist in market i, n_i), learning-by-doing (total number of outlets opened earlier in all local markets, $total_i$), and firm level (dis)economies of scale within period (number of outlets opened in all local markets in this period, d_i).

[TABLE 5 HERE]

We report the structural parameters in Table 5. We find that expected discounted sales increase the probability of entry as they should. The coefficient of 0.3049 indicates that McDs (average) price-cost margin is of that order. The fixed cost of opening the first outlet (= the constant) is 2.72 million 1974 GBP, which seems rather high, but includes not only planning and building costs but also costs of the team engaged in the development plan. If anything, there are economies of scale within a market, as both the number of existing outlets, and its square obtain negative (though insignificant) coefficients. One outlet decreases costs by 90 000 GBP, two by half a million GBP. Notice that these results could reflect not only economies of scale in the fixed cost of opening an outlet, but also (and more probably?) economies of scale in the expected discounted fixed costs of running the outlets. The latter interpretation is possible since we estimate a price-cost margin that is constant over the number of outlets; thus any changes in the price-cost margin that is dependent on the number of outlets in a given market will be reflected in the cost side figures. We find that the local economies of scale expand beyond the individual market, as the (area-weighed) number of outlets in neighboring markets also decreases fixed costs.

At the firm level we find learning by doing: The cumulative total of opened outlets has a linear effect, with the linear term obtaining a negative, the 2nd order term a positive but very small and insignificant coefficient, implying economies of scale / learning by doing.

We also find decreasing returns to scale within a period: The total number of outlets opened within a period increases entry costs as both linear and squared terms carry positive coefficients. These results suggest that even opening the 2nd outlet generates higher costs than opening the first outlet. These coefficients are an order of magnitude smaller in absolute value than the coefficients on the variables representing number of outlets in a given market. However, the firm level effect is likely to greatly dominate the market level effect as it is multiplied by the square of the number of outlets opened across all markets, whereas the within market coefficients are typically multiplied at most by one (as there are rather few markets with more than one existing outlet). Having one previous outlet decreases entry costs by the sum of coefficients of the linear (0.0889) and squared (0.0824) outlet terms, yielding circa 0.17. The firm level effects dominate through the coefficient of the linear term measuring all outlets opened by the firm (total, 0.0065) once 27 outlets is achieved.

5. Conclusions

Although chain-stores arguably started with W. H. Smith in Britain in 1792, they are largely a 20th century phenomenon (Ellickson, 2007). They survive, or even prosper, in the 21st century because they focus on local services and consumer goods - a latte or hamburger are not products bought through the internet, although the internet can tell you where the nearest Starbucks or McDonalds is located. However, their development provides something of a puzzle, because within a reasonably homogeneous population, it must quite quickly become clear that there are profitable locations for the chain, yet developing outlets in those locations takes appreciable time.

Given that services are such a large part of modern economies' GDP, it seems important to further our understanding of the dynamics of this process. Our paper lays out a model that attempts to explain the stylized facts of retail firm expansion through four forces: economies of density in sales and in costs; economies of scale at the firm level, economies of scale over time, or learning by doing, and finally, economies (or rather diseconomies) of openings within a period.

We study a firm that is more straightforward than those studied thus far. In such a case, the importance of detailed specification of the cost side of the equation becomes obvious - if customers in Birmingham, Cardiff or Glasgow are just as likely as those in London to enjoy your product, the reasons for the delay in expanding there must lie somewhere in the cost structure. Unlike Walmart, which is the object of two recent important papers (Holmes 2011, Jia 2008), McD can be argued to have been the only significant producer of over-the-counter hamburgers in the UK from its entry into the country until the end of the 1980s. This means that we can abstract from the main modeling challenge of Jia (2008): Strategic competition between firms. Again unlike Walmart in the US, McD in the UK did not open multiple distribution centers. This allows for a major simplification compared to Holmes (2011). These advantages mean that we can completely model the dynamic (entry) decision-making of McD in the UK by endogenizing both the location and the timing of entry while allowing for entry across local markets to be interdependent.

Our results capture the key features which seem to be generic for service firm expansion. The local economies of scale explain why there is a tendency to expand around existing outlets even if there are diseconomies of density on the demand side as we found. We find that the cost per outlet of opening outlets falls over time, which would by itself suggest an accelerated rate of expansion. In addition, there is little evidence of the learning by doing effect diminishing, perhaps because McD did not reach that part of the learning curve during our observation period, or else that the eventual slow-down in the number of opened outlets is explained by the demand side diseconomies of density and the decreasing attractiveness of those markets without an outlet.

However, this declining per-outlet opening cost is countered by the diseconomies involved in opening a large number of outlets in any time period, so that not all lucrative sites are entered quickly. Presumably, the selection of suitable available sites is difficult and cannot easily be delegated, or scaled to suit. This explains why it takes service firms such as McD and Walmart a surprisingly long time to enter markets that must have seemed profitable early on: If these markets are geographically distant from the existing outlets, the firm cannot reap the local economies of scale in opening and operating outlets in these markets, but does face the within-year diseconomies. It would be interesting to examine whether, with the rapid improvements in geographical IT applications, the pace at which outlets can profitably be opened has now quickened.

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Table 1: Significant events in the early history of fast food outlets in the UK

Date	Event
1955	Wimpy brand established as offshoot of J Lyons, a chain of traditional cafes
1974	McDonalds opens first store in UK
1977	Wimpy chain bought by United Biscuits
1978	Wimpy establishes first counter-service outlet
1982	Wimpy has 35 counter-service outlets (McD has 95)
1983	McD exceeds 100 outlets
1986	Wendy's leaves the UK, selling last 16 restaurants. McD exceeds 200 outlets. McD starts to franchise outlets
1988	Burger King brand (at this time small) bought by Grand Met
1989	Grand Met buys Wimpy from United Biscuits
1990	Grand Met's burger operations separated into table and counter service outlets. Counter service operations mostly rebadged as Burger King. Wimpy International formed with 220 table-service outlets by management buyout from Grand Met

Table 2
Descriptive statistics on outlets and sales

Year	Sales (000s 1974£)	Number of outlets	Markets with at least *n* outlets						
			n =1	*n* =2	*n* =3	*n* =4	*n* =5	*n* =6	*n* =7
1975	558	4	4	0	0	0	0	0	0
1980	1551	51	31	9	3	2	1	1	1
1985	34661	196	147	29	7	4	3	2	1
1990	97446	381	239	74	31	13	6	3	3
Average	32376		90.67	21.00	6.73	3.20	1.93	1.20	1.00
Year	Sales / Population (1974£)	Number of outlet entries	Population in markets with at least *n* outlets (000s)						
			n =1	*n* =2	*n* =3	*n* =4	*n* =5	*n* =6	*n* =7
1975	0.58	3	955	0	0	0	0	0	0
1980	2.63	13	6231	2026	641	369	210	210	210
1985	1.71	32	25487	7052	2447	1597	1446	1187	179
1990	2.51	43	38768	18433	9839	4692	2820	1619	1619
Average	1.91	22.47	15906	5384	2135	1027	767	566	417

Table 3
Estimation results for the sales equation

	1974 – 1990	1974 – 1996	
	1st difference	Levels	1st difference
μ	-1.220	-.583	-.360
	(1.400)	(.709)	(.466)
α	.053*	.042***	.038***
	(.029)	(.015)	(.010)
δ	.683***	.589***	.570***
	(.224)	(.087)	(.150)
Nobs	15	22	21
R^2	.905	.998	.890

NOTES: The reported numbers are coefficient and (s.e.). The dependent variable is McD firm level sales measured in 1975 GBP.

Table 4

Policy function estimation- explaining the entry decision

Variable	Coefficient (s.e.)
lnsales	0.292***
	(0.059)
lnsales sq.	-0.042***
	(0.010)
# outlets in market *i*	0.079***
	(0.031)
# nboring outlets/area	0.907***
	(0.128)
# nboring outlets/area sq.	-0.191***
	(0.058)
total # outlets to date	0.007***
	(0.001)
total # outlets sq. (/1000)	-0.000***
	(0.000)
constant	-2.799***
	(0.101)
LogL.	-1315.253
Nobs.	7735

NOTES: The reported numbers are coefficient and standard errors. ***, **, and * denote significance at 1, 5, and 10% levels.

Table 5
Structural estimates of the per-period profit function

Variable	Coefficient (s.e.)
β_1 Esales	0.3049***
	(0.0972)
θ_0 fixed cost	2.7231***
	(0.1952)
θ_1 # in-market outlets	-0.0889
	(0.598)
θ_2 # in-market outlets sq.	-0.0824
	(0.0579)
θ_3 # nboring outlets/area	-1.0616**
	(0.4647)
θ_4 Total # outlets to date	-0.0065***
	(0.0014)
θ_5 Total # outlets sq.	0.0000
	(0.0000)
θ_6 Within year total # outlets	0.0002***
	(0.0000)
θ_7 Within year total # outlets sq.	0.0029***
	(0.0002)

NOTES: The point estimates have been obtained using M = 250 alternative policies. The alternative policies' policy function parameters are generated as $\theta+0.5\theta\varepsilon$, where ε is distributed N(0,1) and θ is the parameter vector of the actual policy function. We use R = 100 simulation draws, and calculated expected discounted profits (the variable Esales) over T= 100 periods. The standard errors are produced using subsampling using S = 200 subsamples. For the subsample estimates, we use M_{ss} = 100, R_{ss} = 30, and T_{ss} = 100. ***, **, and * denote significance at 1, 5, and 10% levels.

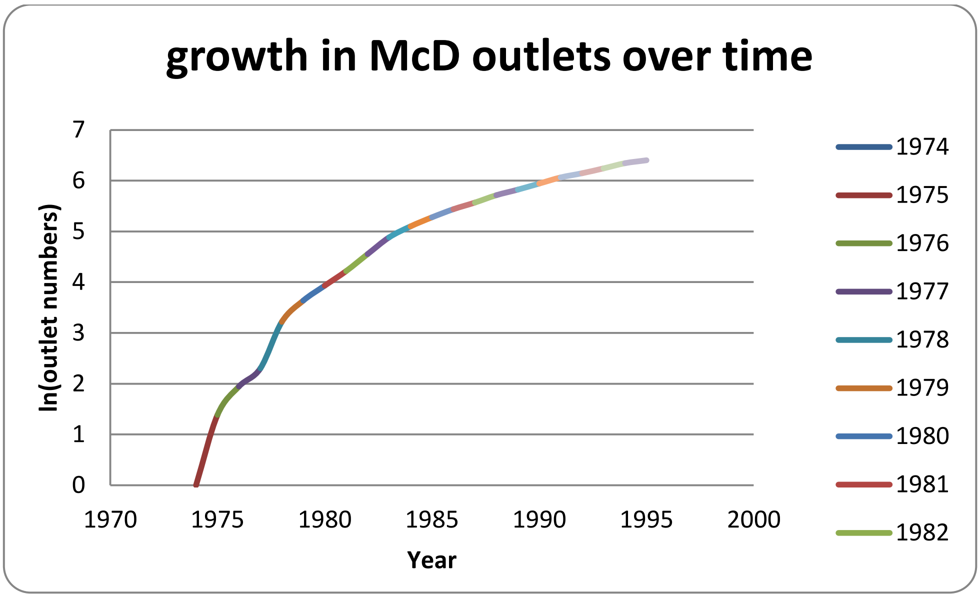

Figure 1: Growth in McDonalds outlets over time.

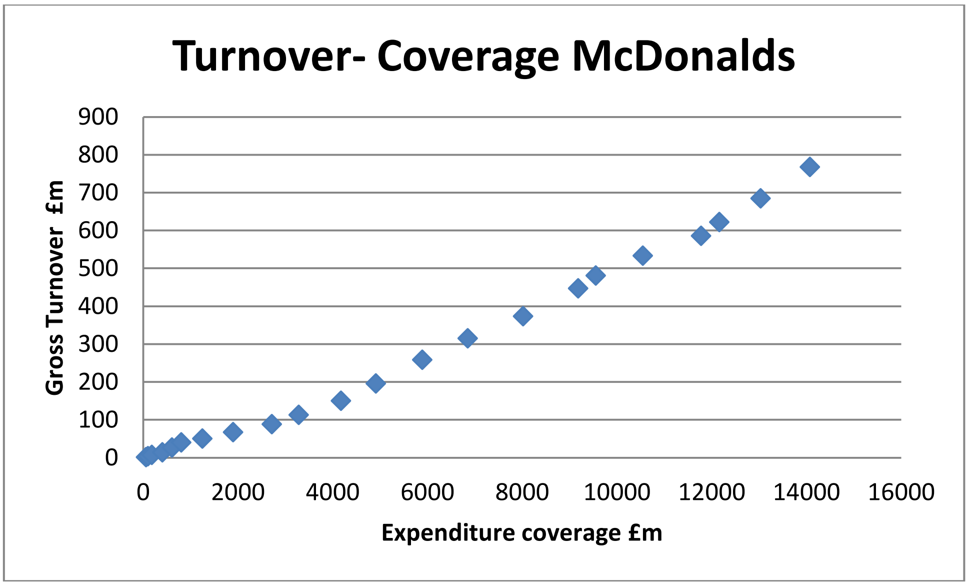

Figure 2: The relationship between turnover and “expenditure coverage”.

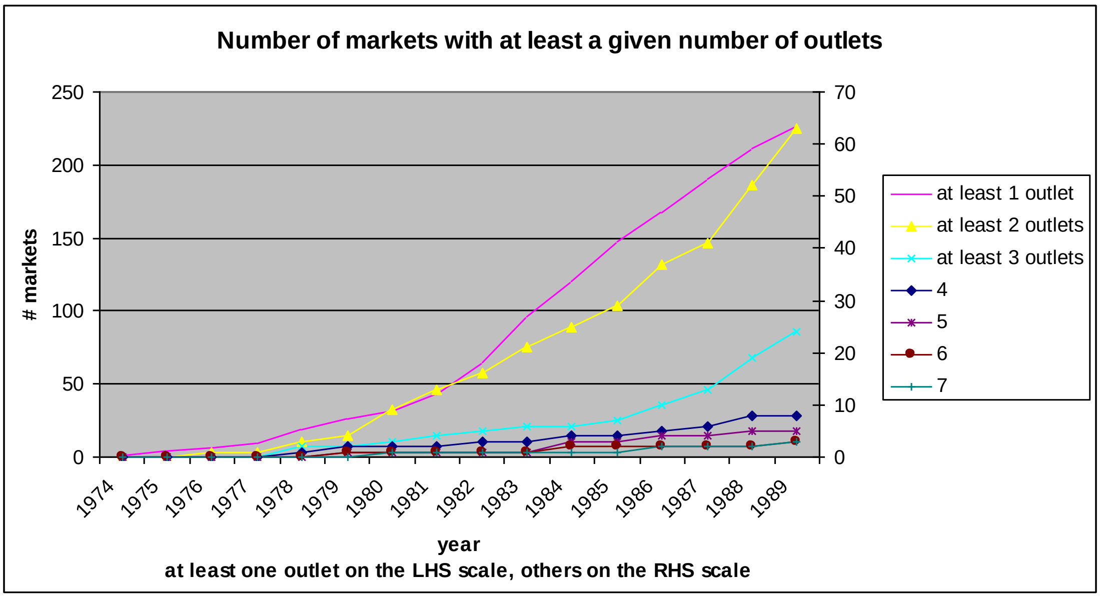

Figure 3: The number of LAD markets with a given number of outlets.

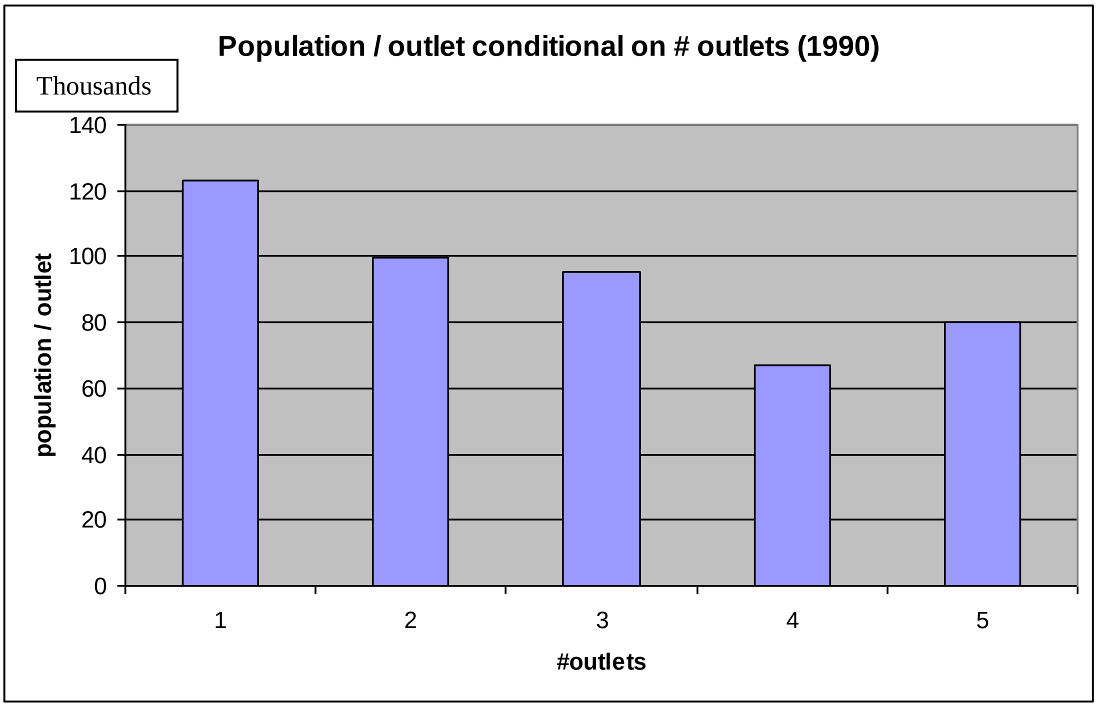

Figure 4: Population served by each outlet, conditional on # outlets.

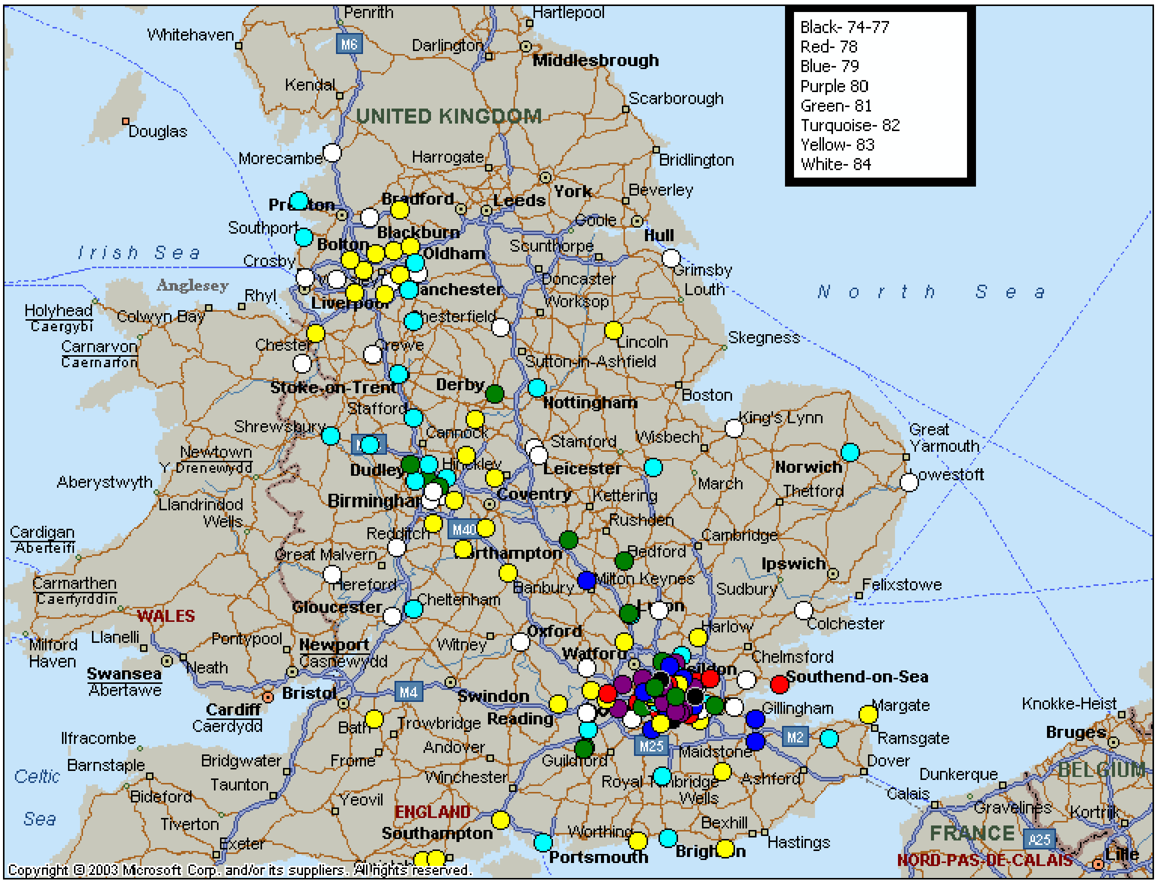

Figure 5: McDonald's expansion pattern over the first ten years.

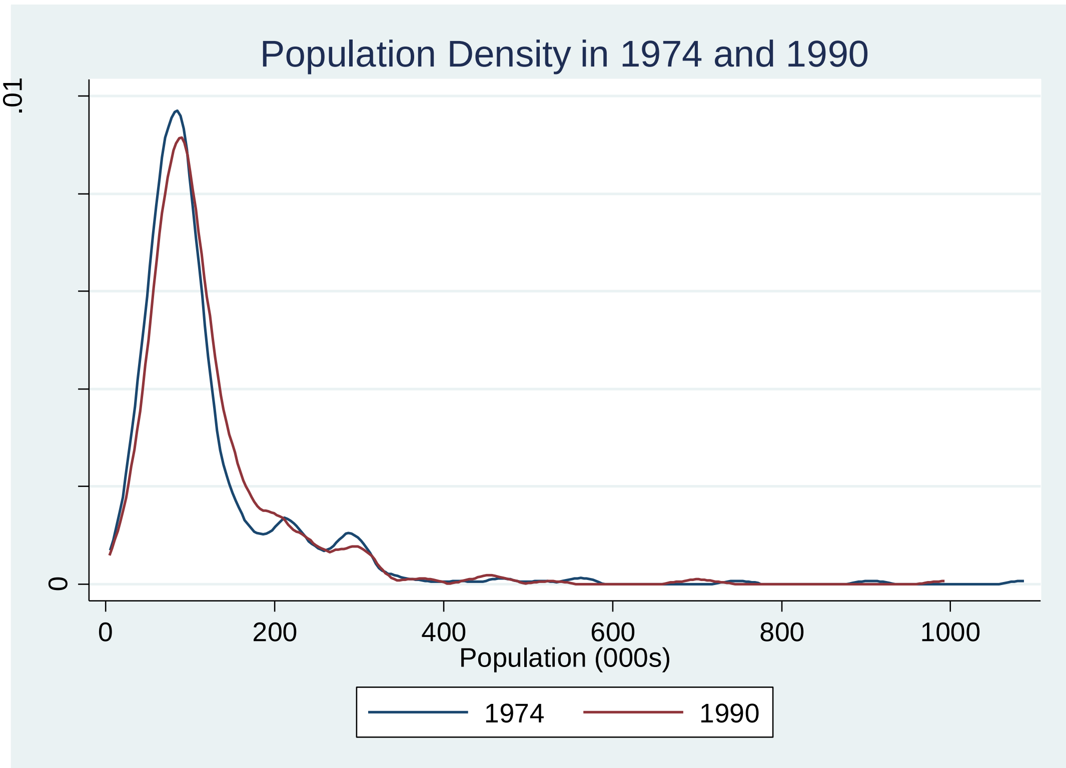

Figure 6: Population density in 1974 and 1990

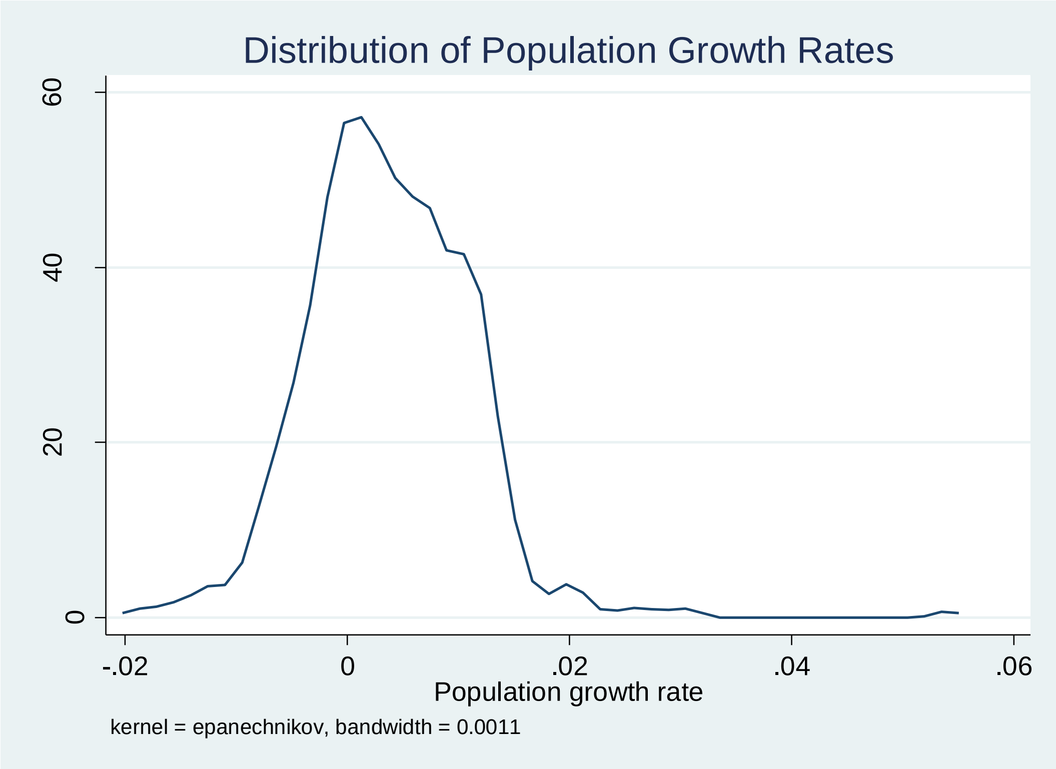

Figure 7: The distribution of LAD market population growth rates

Data appendix

We have collected the data on **McD entry timing and location** from a spreadsheet provided by the firm itself (see Toivanen and Waterson, 2005). We have included all outlets in Great Britain (including London areas excluded in that paper) in this analysis and have checked aggregate numbers by year with the numbers reported in *McDonalds Fact File* 2007. The match is exact, except that one outlet opened in 1982 closed after a few years. We exclude this outlet (on which we have no location information) from our analysis. Beyond our sample period, the number of outlets we record and those recorded in the *Fact File* differ rather more. This is a result of outlets in Northern Ireland, Jersey, etc.

We have collected data on **turnover**, cost of sales, etc, from McDonalds published audited accounts for the UK, as lodged at UK Companies House. These correspond very closely (apart from rounding errors) to the data listed on the *Fact File*, until 1990. Beyond that point, they diverge rather more. We conjecture that the *Fact File* data may include turnover from Irish outlets (which come into existence after our main period). We treat the published accounts data as authoritative regarding UK (actually, GB, since no outlet in Northern Ireland) operations (until 1990).

To this we have matched **data on LADs** from the UK's annual *Regional Studies* for population. This annual publication lists area, population numbers, demographics and a variety of other information. We use the LADs as defined in 1991 and we allocate McD outlets to LADs based upon their (corrected) complete postcodes- an individual postcode relates to a very small area (up to around 15 addresses) in the UK. There are 455 LADs that we include, across England and

Scotland and Wales. Four offshore island groups are excluded from our analysis- the Isles of Scilly, Orkney, Shetland and Western Isles. Each is sparsely populated and is remote from the mainland. Further details may be obtained from the authors.

Neighbors are evaluated as follows. Consider district 1. From a map of the country, the districts sharing a common non-trivial border (not being a single point of contact) with district 1 were established. These are its neighbouring districts. For further analysis, we constructed a 455×455 matrix of neighbor relationships. Neighbours which are such only by virtue of a common piece of significant water are not considered neighbours for this purpose (e.g. districts north and south of the Thames estuary in Essex and Kent).

Per capita expenditure on McDonalds type products is taken as expenditure on "other meat and meat products" plus "soft drinks", from the annual UK Food and Expenditure Survey. Our variable Sales per population in the markets with a McD is this annual figure multiplied by the population in the areas with a McD.

Qualitative factual data on McDonalds (e.g. regarding suppliers) was obtained from McDonalds (1995), McDonalds (2007) and other sources listed in Toivanen and Waterson (2005).