LEARNING AND LOCATION

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LEARNING AND LOCATION

Abstract

We study whether learning from rivals affects within-market location decisions between the two leading competing firms in the UK counter-service burger market, McDonalds and Burger King. In order to do this, we develop alternative models of the location patterns that would be expected if strategic product location were a key factor in locational decision making, and if learning from rivals were the main driver of location. We allow alternatively for the products to be viewed by consumers as identical or as differentiated. To examine the outcomes empirically, we employ three different tests as well as utilizing a reorganization of one of the firms as a quasi-natural experiment. Using detailed location data over time from the two hamburger chains, we find that learning from the other player, coupled with a degree of product differentiation, provides the most convincing explanation for the patterns observed. The implication is that in the market studied, learning influences overwhelm competition effects.

Keywords:

Brand preference; Competitive Strategy; Consumer Learning; Decision-Making; Market Entry; Market Structure; Product Positioning; Retailing and Wholesaling.

I INTRODUCTION

One of the most significant developments in business organization during the 20th century was the emergence of large competing retail chains. An intriguing and central question relating to their development is how these firms decide on the location of new outlets relative to other firms' outlets (Kalnins and Mayer, 2004). Our objective in this paper is to shed light on the relative importance of competition between and learning from rivals in deciding the within-market location of outlets. To do this, we make use of data from the two major fast food chains in the UK. In our data the same firms offering the same products at more or less the same prices face each other in several locations, simplifying the set-up greatly. The evidence we uncover is in favor of learning being a significant part of the explanation, with strategic play being unimportant.

We are by no means the first to study firms' location decisions. A tradition emanating from Marshall (1961) posits reasons why firms of similar types or in similar trades may agglomerate. The first is physical condition, for example the steel cutlery industry in Sheffield arising from access to excellent limestone grit for grinding. But once an industry is established, vertical integration, availability of related goods, improved information flows between firms and also heightened demand, as a result of reduced consumer search costs, reinforce existing patterns (as seen in extreme form with the jewelry industry in Birmingham, England; Florence 1972). Industrial agglomeration has been evaluated by numerous economists, of whom Ellison and Glaeser (1997, 1999) are a prominent recent example; see also Devereux et al. (2004). Other disciplines similarly note the beneficial effects of neighbors when they are differentiated but interlinked ("mutalism", Barnett and Carroll 1987, Baum and Haveman 1997). Organizational contagion (Debruyne and Reibstein 2005) is observationally a similar phenomenon.

It is also appreciated that competition may affect location choice. A longstanding theoretical literature (Eaton and Lipsey 1976, d'Aspremont et al. 1979) developed from the Hotelling (1929) paradigm concludes that firms will spread out strategically in product or physical space in order to relax price competition. Because firms wish to avoid competition being too direct, we must qualify the earlier statements regarding agglomeration. Within any one trade, the greatest advantages arguably arise from being proximate to complementary, not substitute producers (Marshall 1961, p. 227). Reduction of consumer search costs is most direct and effective when it enhances overall demand. To continue the jewelry example to the retail level, grouping together of jewelers' shops in a particular location such as London's Hatton Garden encourages prospective purchasers to visit that location. The adverse effect of this is increased competition. Thus more recently we have seen the construction of malls which contain similar suppliers but not direct substitute suppliers (Beggs 1994).

Several authors, following a tradition coming either from economics, organizational behavior or strategy have examined empirically the location of retail activities such as motels/ lodging (Mazzeo 2002, Chung and Kalnins 2001, Kalnins and Chung 2004) and thrifts (Haveman and Nonnemaker 2000) to test some of these theoretical propositions. For example, within lodging, Chung and Kalnins investigate agglomeration benefits arising through demand externalities or production efficiencies, whilst from a more structural perspective, Mazzeo builds and estimates a model endogenizing firms' product quality choice offerings.

The burden of evidence from this work is that if agglomeration forces are strong, firms benefit by differentiating their *product* offering. If agglomeration forces are weak, firms have incentives to differentiate their offering *physically*, by spreading out in physical space. What we see in our data, somewhat surprisingly, is close physical location coupled with the absence of obvious agglomeration factors. This provides the puzzle we investigate.

To be specific, we track the location patterns of McDonalds (McD) and Burger King (BK) in the 1990s in the UK in terms of timing of entry and co-location distance within markets where they are both present. By the 1990s, consumers in the UK were well used to seeing the products of both companies. Moreover, in the particular markets we study, one of the players had been present for some time. Thus customers had learned about the product generally.

One plausible working assumption is that McD and BK supply products that are perceived to be close substitutes. If products are identical, a theoretical model of location decisions generates sharp predictions on the location pattern of firms. If the products are differentiated in consumers' eyes, we can no longer be as precise about the locational separation pattern. Nevertheless we would expect, for the reasons proposed by those who study lodging location patterns, that McD and BK would pay more attention to prior presence of the other, and be less likely to choose a nearby position, than McD and some other fast food chain, say Pizza Hut.[1] If no real difference is found in co-location patterns between McD and BK and between McD and, say, Pizza Hut, then it may be that the burger products are somewhat different in consumers' eyes and one of the chains *learns* about good locations by observing the other. An obvious alternative possibility is that competition is unimportant relative to other factors, and that the two chains have simply chosen similar locations by using similar processes of site search. Under this alternative, we would not expect location to be affected by things other than locational profitability. Therefore, if we control for profitability, but allow an additional variable to capture the effect of learning from the earlier player, we can isolate whether firms in fact learn from each other.

Our empirical testing strategy involves three steps. First we examine location patterns of burger outlets under the maintained hypothesis that the products are identical. We then examine patterns under the assumption that the McD and BK offerings are differentiated, but not as differentiated as are burger outlets relative to other fast food restaurants. Finally, we examine the hypothesis of learning more directly, controlling for profitability. When we do this, to preview, we do find a significant independent role for inter-firm or "vicarious" learning, as Baum et al. (2000) call it.

There is a strong rationale for studying UK fast food burger chains: We contend that McD and BK were the only strategic competitors in the market in the early 90's; furthermore, they were opening outlets at a fast and increasing pace,

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[1] Indeed, in the lodging case, it has been found that presence of a particular quality of motel has encouraged the next entrant to choose a different, lower quality image (Kalnins and Chung 2004).

creating variation over geographical markets, without price variation. We have been able to gather detailed outlet opening data and precise locations. Reasonable geographical proxies for local markets are available, as are socio-economic variables characterizing these markets. Most importantly, it can be argued that BK's expansion possibilities experienced a discontinuity in 1990, due to firm reorganization. Thus we can examine the effects of McD location on BK location choice in (that subset of) markets where there are no previous BK outlets. This quasi-natural experiment allows us to test an implication of learning that is not affected by other possible determinants of location choice.

An additional reason to study fast food is that among industry practitioners, the importance of inter-firm learning seems widely accepted. This was corroborated in our discussions with industry representatives, and comes through in a recent Wall Street Journal article (Leung 2003) and a recent book (Rubinfeld and Hemingway, 2005). Leung describes how a firm uses information about rivals' location and how the agent for a fast food company pays special attention to a rival that 'serves as a good benchmark' for her client company because they aim at the same customers.[2] Leung also describes how the agent monitors rivals' outlets and their performance, and how these affect location recommendations.[3] Rubinfeld[4] and Hemingway argue "It's true that sometimes the presence of multiple competitors helps everyone's business by drawing more total customers. … There is always a *reason* for this kind

[2] To cite the article: "She pays particularly close attention to Wendy's International Inc., which markets itself as the upper end of fast food and thus serves as a good benchmark for Arby's."
[3] Another cite: "Checking that against her maps, she got some good news: There are no other Arby's in the area -- and one nearby Wendy's generates 24% higher sales than the chain's average."
[4] Rubinfeld was the architect of Starbucks' expansion process.

of synergy to occur, usually based on differentiation. … Locate close to a competitor only if you can differentiate yourself." (pp. 234-5)

Our plan is as follows. In the following section, we briefly discuss the relevant theories affecting location decisions of firms. In the third section, we describe the industry and the data. Section four explains our testing strategy and contains our tests, and section five concludes.

II THEORY

1. Product location

Irmen and Thisse (1998) show in a tightly parameterized model of multi-dimensional product differentiation that rivals want to locate their products (=outlet-product(s) bundles in our case) close to each other in all but one dimension of product quality. In this, the most important dimension, they maximize differences. In the context of the UK it is clear that price is not a major component of competition at the local level; in fact prices are essentially national.[5] Assume for a moment that location or distance is the most important source of product differentiation between the two firms in our sample, and consider a market where prices are fixed and where firm A opens two outlets and firm B one.[6] Both firms attempt to maximize the area they cover, subject to the other player's moves. There are two rather different cases, one (AAB) where A locates two (or more) outlets before B locates its outlet; the other (ABA) where B

[5] Here we note that there is an important difference between the UK and the US. In the US (see e.g. Thomadsen 2002) managers/franchisees of individual outlets have considerable pricing freedom; this is far less true in the UK.

[6] Clearly, we cannot develop hypotheses relating to relative distances without at least two outlets of one player and one of the other. See Narasimhan and Zhang (2000) for a formal model of entry into an untested market under competition.

locates second after the first A store has opened. In the first, the game is essentially two-stage whilst the ABA case involves a three-stage game. We model these in more detail in the Appendix. The equilibrium predictions on distance are as follows: The AAB case either has distance $0.5A_1A_2=A_1B$, or (more generally), $\max(A_1B, A_2B) =A_1A_2$.[7] In the ABA case the prediction is that $A_1A_2 \leq A_1B$. Neither prediction assumes a uniform distribution of custom across space, although symmetry (about the center) in the distribution is assumed.

As an extension of this hypothesis, if another chain produces a significantly different product from McD (say, a pizza range), the Irmen-Thisse model predicts a location physically closer to the first McD than are subsequent McDs, assuming the first McD location was well chosen. It is also more likely that a pizza restaurant locates near McD than that BK locates close to McD, assuming the products of different burger chains are closer substitutes than are burgers and other fast foods.

2. Learning

The learning story we have in mind builds on two different literatures. On the one hand, the economics learning literature (see e.g. Caplin and Leahy 1998) shows that firms may want to locate close to each other because later arrivals learn from the early arrivals about the profitability of the location. On the other hand, the management literature suggests that firms learn 'vicariously' from each other. As Baum et al. (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…".

[7] This latter prediction is consistent with the model of Joseph (2003).

Naturally, learning can occur only from early outlets to later ones. Hence, if learning as described above is important, but strategic product location decisions between players are not (i.e., are relatively less important than learning), the prediction in the AAB case is that min(A_1B, A_2B) <A_1A_2, although it is more likely that the first distance, A_1B, is the smallest. This is different from the product location prediction, but might not be clearly distinguishable from it empirically. The prediction in the ABA case is that distance $A_1B < A_1A_2$, a prediction clearly testable against the product location hypothesis.

In Section IV.3 we discuss how a standard decision theoretic framework suggests that the longer the first McD has been in existence, the more likely it is that BK chooses a nearby site, if (Bayesian) learning is taking place.

III DATA

1. The Industry

Our data come from the UK fast food burger industry. As detailed in Toivanen and Waterson (2005), for the early 1990's at least, this industry is structurally very straightforward. One can argue that there are only two players large enough to be considered strategic: McD and BK. The third largest burger firm, Wimpy, was excluded from the counter service market both by contract (a contract between Wimpy and BK precluded Wimpy from opening over the counter outlets before June 1993), and it seems, by choice (by end of 1994, all 240 Wimpy outlets were table seated, by mid-1996 it had grown only to 272 outlets, and in 2001 still had less than 300 outlets; its marketing budget is an order of magnitude smaller than the other two). Table 1 outlines the development of our two firms and the industry. What is important to us is that since its entry into the UK in 1974, McD has grown steadily and consistently by opening new outlets of its own. BK as it now exists, in contrast, is the outcome of a complicated story where two relatively small competitors (BK and Wimpy) are first merged and then partly separated. The outcome was that by 1990 BK emerged with a clearly larger number of outlets, and larger resources for expansion.

TABLE 1 HERE

It is important, in the British context, to have in mind a picture of the "typical" location of a fast food outlet within the district at the time of our study. This is not in a mall (i.e. a confined and defined space), nor in a drive-through edge-of-town location. Rather, it is on a high street, within a traditional shopping area that lacks tightly defined boundaries.[8]

Another characteristic of difference between outlets in the UK and those, for example, in the US (see Thomadsen 2005) is that price competition between outlets within a chain is extremely muted. It is common for both BK and McD national television advertising campaigns to feature price information on particular fast food items (albeit always with the necessary legal caveat "at participating restaurants").[9] Furthermore, encroachment is not a contentious issue in the UK (unlike in some US States; Kalnins 2004). McD's contracts typically offer the franchisee a site the

[8] Specifically, the modal McD outlet in the data set we use is of this type. For example, all but seven of the 57 first outlet McDs are in a high street location, several of them actually on a street with this name!

[9] At time of writing, the McD's UK website lists prices for a range of menu items including a "Happy meal", a cheeseburger, etc. BK's UK website also features a range of prices including the price for its signature product, the Whopper. By coincidence, the Happy Meal and the Whopper are identically priced.

company has developed, and are explicit in excluding legal claims from franchisees regarding subsequent openings.[10]

We take the relevant markets, within which competition will be examined, to be represented by Local Authority Districts (LADs). LADs are administrative and planning districts, largely centered on a particular town, that reasonably well proxy for markets. Socio-economic data is available at LAD level on an annual basis.[11] Table 2 shows that they vary a good deal across a number of dimensions such as population, leading to very different degrees of penetration by our burger chains. Our main task here is to match company outlet[12] data to postcodes and thence configurations within LADs.

TABLE 2 HERE

2. Outlet locations

As we are interested in within market location, we calculated the distances between outlets in our chosen markets. Using the facility on http://www.streetmap.co.uk/ for converting postcodes to Ordnance Survey grid co-ordinates, each was mapped to a co-ordinate[13] and the Euclidean distance between outlets calculated. Because we are interested in relative locations, we selected markets fulfilling the following three criteria into our sample:

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[10] The source of these last observations is inspection of the set of agreements registered with the Office of Fair Trading under the provisions of the Restrictive Trades Practices Act 1976 and subsequent legislation. Files numbered 6193, 6194, 15127 and 15678 contain examples.

[11] These data largely come from Regional Trends or its sources; see the Data Appendix to Toivanen and Waterson (2005), available at http://www2.warwick.ac.uk/fac/soc/economics/staff/faculty/waterson/publications/.

[12] All McD data was received from the company itself. For BK, we received the addresses of all their outlets as of end of 1995, and for a proportion, the opening dates. For the rest, we collected the opening dates from a variety of sources. See again the data appendix to Toivanen and Waterson (2005)

[13] Each UK postcode covers no more than 15 addresses, roughly a block or less. Coordinates thus generated are accurate to within 100 meters.

a. Both key players (McD and BK) are in the market[14] at the end of our period (end 1995).

b. We can date order which player was first into the market, and determine the ordering of outlets up to the point at which the other player entered.[15]

c. There are at least three outlets associated with these players in total.

From the set of 57 markets fitting these criteria, we stopped recording outlet details regarding location (i.e. their postcode) once the second player had entered for the first time. This set of districts is divided into three subsets. In the first, consisting of the first 33 observations listed in Table 3A, there are three or more outlets (up to 6), of which only the most recent is the outlet of a different firm than all previous entries. In the second set, the next 19 observations (Table 3B), there are three outlets, with the chronological order of outlet openings by firms A and B being A, B, A, (or in four cases, either A, B, A or A, A, B).[16] There is then a final set of five A, B, B cases, of limited use (last rows in Table 3B). We use different subsamples of these data. Some key distance and firm statistics are shown at the foot of Table 3. By comparison with Table 2, we note that on average, the included districts are around 1/3 the area of the average district. Larger, typically rural, LADs mostly have few or no fast food outlets. It is noteworthy that there is a very significant difference in Table 3 between the median distance between same-firm outlets and different-firm outlets.

TABLE 3 HERE

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[14] Note that we look to close competitors within markets (LADs), not across them. Since LADs are normally centerd on a particular place, the most direct competitors are likely to be within that place.

[15] This task is simplified by the fact that there is almost no exit by either firm.

[16] In these four cases, we are unsure of characterization since the second and third outlets open in quick succession, but they logically appear in the second subset, so far as our location hypotheses are concerned.

IV EMPIRICAL TESTS

Our testing procedure involves some novel features and consists of three stages as follows. Essentially, outlets may be differentiated by location, or by different product mix (or both, but Irmen and Thisse suggest this is unnecessary). If consumers view the products as substantially the same, and spatial location is the key differentiating feature, outlets will be kept apart by the need to gain sufficient market share to make operation worthwhile. Thus if in consumers' eyes McDonalds and Burger King offer essentially undifferentiated products, the same logic that dictates the spacing of McDs' own outlets will apply to the relationship between McD and BK outlets, except that they are different strategic players. In this first stage test we can be fairly precise about location patterns measured as relative distances. However, we find these patterns are not replicated in practice in our sample; instead, the relative locations are much more in conformity with learning.

Alternatively, if McD and BK are seen as offering sufficiently differentiated products so that they are just two amongst a group of fast food chains, the logic that dictates spacing between McDs' outlets will not apply to BK. However, we may expect patterns in common between BK and outlets of other fast food chains in their relationship to McDs' outlets. Here, the evidence is mixed. This finding does not bear directly on what in fact determines BK's location if product differentiation rather than locational differentiation is the driver, although the pattern that exists is suggestive. Two obvious contender explanations are that learning, say from McD, suggests appropriate locations (in line with Leung, and Caplin and Leahy), or that there is some other, unmeasured, feature that causes the locational pattern. We attempt in the third stage to distinguish these explanations by employing proxies for learning and profitability of locations in the explanation.

Finally then, we test an implication that is unique to the learning hypothesis by running regressions explaining the distance between the first McD outlet and the first BK outlet using market level controls and the rank of the McD outlet in question, together with the time it has been in the market prior to 1990. The idea is that the rank of the outlet controls for location specific demand, and the time in the market prior to 1990 is a measure of learning. Specifically, the time in the market is a measure of the strength of the signal[17] to BK. BK could, thanks to its reorganization, more effectively use this information after 1990 than prior to it. We find that, ceteris paribus (especially, controlling for the profitability of the location of the first McD), the longer the first McD outlet has been in the market prior to 1990, the closer BK locates to it. This result supports the learning hypothesis, under the assumption that a longer observation period translates into more signals (and therefore more Bayesian updating). The result proves robust to a number of issues like collinearity between our profitability and learning variables, length of the learning period, and definition of the profitability variable. Taken together, these findings suggest that even a firm like BK, which has great experience in opening outlets, resorts to between firm learning when deciding where to locate its outlets, and that this effect more than outweighs the effects that smaller distance has on competition between firms. This evidence is also in line with the informal accounts of how (fast food)

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[17] More accurately, a measure of how many draws from the sampling distribution of profitability BK has been able to obtain. This can be formalized in a standard model of Bayesian learning.

service firms operate. In all three test processes, we select samples most appropriate to the particular test.

1. Product location

Consider the first subset of 33 markets with three or more outlets. Here the maintained hypothesis is that products of the two firms are "close" substitutes. If strategic product location is the relevant determinant of location, we expect $\max(M_1B, M_2B) \leq M_1M_2$ to hold. By pure chance (random locations), this would happen 1/3 of the time. In fact, it occurs in only 13 of our 33 cases. We cannot reject the Null hypothesis that this observation is not significantly greater than expected by chance (z=0.55). If learning is the relevant determinant of location, we expect $\min(M_1B, M_2B) \leq M_1M_2$. This occurs in 27 of the 33 cases. However, by chance it would occur 2/3 of the time. The hypothesis that 27/33 is a significantly higher proportion than 2/3 yields a z-value of 1.66 and can therefore be accepted at the 5% level on a one-tail test. While not decisive, the evidence in this subset is more in favor of learning than of strategic product location.

Now consider the second subset of 19 markets with three outlets each. Here we have a direct comparison across theories, with strategic product location predicting $A_1A_2 \leq A_1B$, whilst learning predicts the complement, $A_1A_2 > A_1B$.[18] A raw count of cases yields a remarkably clear result - 18 of the 19 cases are in line with the learning alternative, a significant proportion at almost any level. Pursuing this further, we can alternatively test the difference between mean and median distances across the A_1A_2 and A_1B pairs. As seen in Table 4, there are large numerical

[18] Note it is not always McD that is first into an area. We treat the two cases where BK is first as equivalent.

differences between these mean and median values. So far as means are concerned, $A_1A_2 > A_1B$ is easily accepted over the Null, with the t-value being 4.07. As regards medians, the chi-square value of 15.16 clearly allows us to reject randomness. Thus this second sub-sample provides strong evidence in favor of learning.

TABLE 4 HERE

However, it may be that the products of McD and BK are very distinctively different, so far as consumers are concerned. Our test of product differentiation involves looking at the distances between McD and BK, McD and KFC, and BK and KFC, and similarly between the hamburger firms and Pizza Hut and between them and the table-service hamburger chain, Wimpy (thus including all chains of any significance in the fast food market). Our prior is that the two hamburger firms are closer together in product space than either is to KFC or Pizza Hut.[19] If this were so, then on the argument of Irmen and Thisse (1998) we would expect that KFC and Pizza Hut locate closer to the hamburger firms than these to each other, under the maintained hypothesis that a 'best' location exists.

Here we simply utilize data on presence as of 1994. These come from the source *Retail Directory of the UK*. This provides a street-by-street listing of retail outlets in most major UK town centers, from which we extracted information on the additional chains of interest. Therefore, in this analysis, we restrict outlets under

[19] It has been suggested to us that consumers do view the products as very different- that they either patronise McD or BK, but not both. However, this is strongly inconsistent with survey evidence, for what it is worth. A report by a market research company, Mintel (1998), details information that allows us to calculate lower bounds for the overlap between McD and BK customers by reporting what percentage of their sample i) has visited any hamburger restaurant in the last three months, ii) McD, iii) BK. By assuming that all those that visited a hamburger restaurant but did *not* visit McD did visit BK, we can calculate that over all customer groups, at minimum 73% of those consumers in the Mintel sample that visited a BK outlet also visited a McD outlet. This overlap in customers is, incidentally, much greater than that between McD and Pizza Hut or KFC.

consideration to those that appear in a town center.[20] In order to make the tests meaningful, we restrict our sample to those town centers where three or four of the players appear.

As Table 5 shows, this distance data is noisy. A series of comparisons are available. In the upper panel, these are performed using absolute distances within matched sub-samples. In the lower panel, we bring distance to a common base, so we analyze relative distances within maximally sized sub-samples. Arguably, the median provides the best method of comparison in this table, since (BK/McD) outliers where the nearest outlets are some kilometers apart affect all the means. Looking first at the three-way comparison between McD, BK and Pizza Hut, we might expect under product differentiation that the first McD-BK distance (denoted MB) would be greater than the other two. However, it is almost identical to distance between McD and Pizza Hut (MP). By contrast, the three-way comparison involving KFC does provide some support for the product differentiation hypothesis. Yet, turning to the comparisons involving Wimpy, no support is offered, since the MB distance is smallest.

Now turning to the lower panel, the values listed are taken as a proportion of the "diameter" of the LAD, assuming it approximates a circle. Thus for example, the median distance between McD and Wimpy outlets across 20 cases is less than 2% of the diameter of the respective districts. The main feature coming out of this comparison is that the median proportional distances are *all* small, save that between successive McD outlets, which is significantly larger.

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[20] The town center is a sub-element of a local authority district. Where there is more than one McD or BK, we took the min of the distances. As the data shows, the other chains are less extensive than McD and BK.

Taken together, this second set of tests suggests that product differentiation can be a partial explanation of the location patterns we observe, with the twin caveats that i) the data are too noisy to allow statistically significant conclusions, and ii) it could be that the best location for hamburgers is not the best location for other types of (fast) food. The latter point probably carries less weight in the UK than North America, as the locations are almost without exception along the 'high streets' of towns, as explained earlier.

TABLE 5 HERE

2. Learning

The above tests produced evidence that BK locates closer to the first McD outlet than we would expect if strategic product location, or pure chance, explained the location patterns. Our suggestion is that this pattern is due to learning, which is necessarily coupled with the assumption of some degree of product differentiation between the firms.[21] An informal description of practical location procedures (in the US) is given in Leung (2003), "In the past, many restaurants simply followed the growing highway system, or plopped themselves next to McDonalds to piggyback on the No. 1 burger chain's market research." The question, discussed below, is how we can identify learning.[22]

We should recognize the possibility that the first McD outlet is located in a particularly profitable location and that this, not learning, is the reason for BK placing its (first) outlet close to the first McD. For this to be true, we need to provide

[21] Even if learning led BK to perfect knowledge of the profitability of a McD location, if competition was perfect post-entry then entry would not pay even with small entry costs.

[22] Leung's article clearly suggests also that closeness to *a* relevant competitor is necessary, but not sufficient.

an explanation why the location of the first McD would consistently be better than that of subsequent McD outlets.

One plausible scenario is the following: assume that demand for fast food (hamburgers) in the UK ever since the mid-70s has increased at a constant rate both between and within markets. Assume also that within market differences in demand are known. Assume further that even a firm like McD faces constraints as to how many outlets per period it can open, or alternatively, that the costs of opening an outlet in a given period are convex in the number of outlets opened in that period. What would be an optimal entry strategy in such circumstances? According to this story, McD could already in 1974 when it entered the UK rank all the possible outlet locations in terms of profitability. It would however not be optimal to enter all locations right away, as this would increase costs of entry compared to the alternative of opening in some locations in the following year(s). It would be optimal to open in the best locations first. If this is the strategy McD has followed, then the first location in each market is the most profitable location in that market. Our findings reported above would then simply provide evidence that BK, too, is able to rank locations within (and between markets), and therefore locates close to the first McD outlet. No inter-firm learning need be involved. We test this story against the learning alternative.[23]

The theoretical justification for our test of learning comes from standard Bayesian decision theory. It can be shown that, conditional on the draws being

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[23] It is possible that there is also consumer learning, where McD 'educates' consumers to consume its hamburgers. There is some evidence consistent with this in Toivanen and Waterson (2005). However, it is most unlikely that McD educates consumers to like BK hamburgers! Also, at the time most of our entries were taking place, hamburgers were hardly a new phenomenon in British cuisine.

positive (higher than the prior) on average, the posterior of an experiment with a larger number of draws is larger on average than that of an experiment with a smaller number of draws.[24] Further, this difference is growing in the difference in the number of draws. In our data, the inability of BK to exploit information prior to 1990 gave it a chance to sample from different distributions, i.e., observe the profitability of the first McD outlets in different markets. The number of draws available to BK varied over markets depending on when McD had opened the first outlet, giving us observable variation in this metric. Also, the fact that BK tends to locate close to the first McD is evidence for the draws (signals of profitability of the location of the first McD outlet) being on average higher than the prior. Our hypothesis is thus an implication of Bayesian decision making: the larger the number of draws (the longer the first McD was in existence prior to 1990), ceteris paribus, the higher the mean posterior, and therefore, the more likely it is that BK locates close to the first McD outlet.[25]

Our understanding of how learning takes place is nicely described in Leung (2003). Her story confirms what we heard in discussions with UK industry representatives. Firms hire agents to scout for attractive locations. These agents collect demographic information on potential sites; visit them, paying special attention to both the existence of rivals and the existence of providers of complementary products (e.g. supermarkets in the US). They also pay attention to

[24] Assuming the same prior mean and precision for both or all locations, and the same mean and precision for the draws. See e.g. de Groot (1970, p. 167). Another implication of the model is that the precision grows in the number of draws, strengthening our argument further.
[25] With hindsight, since McD exits so infrequently, we can say that the mere presence of a McD is an indicator of some level of profitability. Yet profitability clearly must differ between stores and some markets will be insufficient to support a close competitor.

relative differences in performance of different outlets of the same rival chain. They collect the information for example by visiting the outlets of rivals, and by monitoring their customer flows. All these are ways of collecting information that to us seem to provide more accurate information, the longer the time period over which this information was collected. For example, outlet-level performance can vary both over the year and seasonally depending on the location. In our data, BK was in a position to utilize this data concerning a period of time the length of which varied by McD outlet in question, without being in a position to act on the information prior to 1990 to the same extent as later. This creates a quasi-natural experiment regarding the amount and accuracy of information that was available to BK by the time it got the resources to expand on a larger scale.

Our tests exploit an implication of the above story of how the profitability of the locations of first McD outlets varies over markets, providing us with a way of controlling for differences in the profitabilities of the first McD outlets. They also test an implication of learning that should not be found in the data if product differentiation is the sole determinant of location. If McD behaves as outlined above, then the ranking of McD outlets is an exact (but ordinal) measure of the relative profitability of McD outlet locations. Further, if BK has used presence prior to 1990 to observe the profitability of different (first in the market) McD outlets, then the time a McD outlet has existed prior to 1990 is a measure of the number of draws BK has been able to sample for a given McD outlet. We therefore take all markets where McD has at least two outlets by the time of BK entry, and estimate the following regression:

(1) $$dist_{m1,b,i} = Z_i \alpha + X_i \delta + \beta_1 time_{m1,i} + \beta_2 rank_{m1,i} + \varepsilon_i \, .$$

In (1), dist is the distance (in meters) between the first McD outlet and the BK outlet in market i, Z is a vector of variables controlling the locations and count of McD outlets, X is a vector of market characteristics that controls for observed differences between markets, time is the (log of) time prior to 1990 that the first McD outlet has been in existence in market i, and rank is a measure of the rank of the first McD outlet in market i.

TABLE 6 HERE

Our results are presented in Tables 6 and 7, the difference being that in the latter, we include a vector of market characteristics as controls. In Table 6, our controls are the number of McD outlets in the market by 1990, and the distance between the 1st and 2nd McD outlet. The former controls for the overall (revealed) attractiveness of the market, the latter - in addition to the direct controls of rank of 1st McD and its square - for the relative profitability of the location of the 1st McD outlet and for overall market density. The more tightly centered a market is, the closer one would expect the 2nd McD outlet to locate.

In the first column, we regress distance between the 1st McD and BK on (log) time, our learning variable together with these controls and the rank and the squared rank of the 1st McD outlet. We find that time obtains a negative and significant coefficient in line with the learning story: the longer BK has observed the 1st McD, conditional on its rank and the other controls, the closer BK locates. Notice that the coefficient of the distance between the 1st and 2nd McD is positive and significant. As a robustness test, we have also used a bootstrap to estimate confidence intervals for our point estimates. It is well known by now that, especially in small sample, a bootstrap may offer better estimates of confidence intervals than analytic approximations (Horowitz 2000). The linear rank coefficient is negative as we expected: the lower in rank the 1st McD outlet, the further away BK locates. This suggests that rank does indeed control for profitability. The squared rank carries a positive coefficient, significant at 10% level. The coefficient on the number of McD outlets is negative, but not significant. In column (2) we repeat the exercise, but take issue with the correlation between our learning (= time) and profitability (=rank) variables by orthonormalizing the former with respect to the other explanatory variables. The idea is to leave us much variation in the rank variable as possible. The results are the same otherwise, but the linear rank coefficient is roughly halved in absolute value, and only significant at 11% level. Squared rank is also significant only at 11% level. Removing the correlation between the rank and the learning variables thus has no effect on the learning coefficient. In column (3) we checked the robustness of our results against the possible critique that the benefits from observing an outlet decrease fast, i.e., after a number of years, and therefore an additional year of observation (even if forced, as in BK's case, due to constraints in capacity to open new outlets) yields no new information. Our base specification already takes this into account by using the log of time; in column (3), we cap the amount of time at ten years.[26] Our results are somewhat strengthened quantitatively. Finally, column (4) reproduces column (3) using an orthonormalized learning variable. The coefficient estimate for the learning variable is close to those in columns (1) and (2).

[26] Experiments with other cut-offs (seven, five) produce similar results.

TABLE 7 HERE

To check the robustness of Table 6's results to observable market characteristics, we add a vector of those in column (1) of Table 7. We also add time squared. Including population, area, proportion of under-16's and over-65's, a London dummy, and the number of McD and BK outlets in neighboring districts in 1990 results in a negative, but insignificant time (i.e. learning) coefficient. The added controls are not jointly significant: Of them, only Youth and Pension carry significant, positive, coefficients. Dropping those variables with an insignificant coefficient (all but Youth and Pension, see column (2)) results in a significant and negative learning coefficient. Squared time carries a positive but insignificant coefficient, and both rank variable coefficients are insignificant. The linear rank coefficient is negative and significant, and close in value to that in column (1) of Table 6. In column (3) we re-estimate column (1)'s specification using an orthonormalized learning variable.[27] Now the learning coefficient is negative and significant, and pretty close in absolute value to those reported in columns (1), (2) and (4) of Table 6. In column (4) we change the rank variable: instead of using a step function that increases by one after each 50 outlets, we use the actual rank. The linear time coefficient is negative and significant at 11% level; the squared time coefficient is negative and highly significant. The rank coefficient is negative and significant, and lower in value compared with the other columns (as expected). Throughout Table 7, the coefficient of the distance between the first and second McD remains stable and highly significant.

3. Caveats

[27] The normalization is the same as used in Table 6.

We have performed three different tests on determinants of location of McD and BK outlets. Taken together, the tests provide no support for the strategic location explanation, weak support for the product differentiation explanation, and good support for the learning explanation. There are however a number of caveats that need to be acknowledged.

First, the samples we use are small. This small sample problem affects the product differentiation test most: There, no firm conclusions could be drawn. While there is little we can do in this regard, we think it unlikely that the smallness of the sample(s) would bias the results in favor of learning in either of the two tests we use that involve learning. The two reasons we have for this are that 1) while the data in the two tests overlap, the samples are different and 2) the tests rest on very different approaches, and use – apart from distance of course – very different features of the data. A second caveat is that each of the test procedures involves assumptions that are impossible to test with the data we have. So for example, it is unlikely that McD and BK produce exactly identical products, and if one took the view that the products were substantially different, this could nullify our first test. Here, our approach has been to implement a range of different tests in order to bound the effects: For example, the learning implication in the third test should not be affected by the degree of product differentiation between the firms (as long as the firms' products are at least to some degree substitutes). Third, one may object that despite our efforts to control for differences in the profitability of the first McD locations in the third test, we haven't quite succeeded in this. Then an alternative interpretation of our finding that time between opening of first McD outlet and 1990 has a negative effect on the distance between the BK and the first McD outlets is that, even after conditioning on our profitability controls, the true profitability differences between first McD outlets correlate negatively with the opening time. That is, the finding we interpret as learning might actually be driven by relative profitability differences between locations of first McD outlets. Finally, one may be concerned that our sample suffers from selection. Because of earlier results with this data, we think there is little reason to worry that preemption would have caused sample selection. Obviously, we condition our data on there being at least three outlets, and these markets may not be representative of all markets. Yet clearly, competitors' location decisions within a market need to be conditioned on both rivals being present. It is quite possible that some markets that had just one firm in 1995 when our observation period ended by now have both firms present. However, it is hard to see how this temporal truncation would bias our distance results especially after conditioning on observable characteristics of the markets.

V CONCLUSION

Although the evidence provided in this paper is of only two firms in one national market, the flavor is clear: we establish that BK consistently locates closer to the *first* McD outlet than we would expect if strategic product location or pure chance (such as local planning restrictions) were driving the location decisions. We also find that the distance between the first McD outlet and the BK outlet is negatively affected by the time the first McD outlet has been in the market prior to 1990, conditional on the rank of the McD outlet. All this suggests that in making its location decisions, BK learns from (the first) McD, and that this effect overwhelms other effects on location. Our finding is different from but consistent with the view and evidence (see Thomadsen 2005, Kalnins 2003) that there is a surprising degree of product differentiation in customers' minds between McD and BK. This is because a close location is profitable only if competition is less than perfect.

The implication from a marketing standpoint is that the two players have managed to develop sufficiently distinctive images that close locations are sustainable without over-crowding the market and without inducing price competition. The evidence is consistent with the second player benefiting from having observed the first player's location. This inter-firm learning is in turn consistent with practitioner accounts of location choices.

The implication from an industrial organization viewpoint is that notwithstanding the importance of (strategic) competition in many oligopolistic markets, inter-firm (knowledge) spillovers may be of overriding importance even for firms that have invested a great deal into solving the problems relating to optimal product positioning in the markets they serve.[28] Finding that such spillovers outweigh strategic considerations in fast food retailing is rather novel.

[28] It could be said that the outcome is unsurprising given the lack of price competition in the UK fast food market. Yet this absence of aggressive price responses is clearly not a primitive.

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Table 1
Key dates in the UK history of burger retailing

Date	Event
1960s	Wimpy brand established as offshoot of J Lyons
1970s	Wimpy established limited counter service concept
1974	McDonalds opens first store
1977	Wimpy chain bought by United Biscuits
1983	McDonalds exceeds 100 outlets
1986	McDonalds exceeds 200 outlets
	McDonalds starts to franchise outlets
1988/89	Burger King brand (at this time small) bought by Grand Met
1989	Grand Met buys Wimpy from United Biscuits
1990	Burger King has 60 outlets
	Grand Mets burger operations separated into table and counter service
	Counter Service operations mostly re-badged as Burger King
	Wimpy International (with 220 table-service outlets) formed by management buy-out from Grand Met
	Grand Met insists on 3 year agreement preventing Wimpy opening counter service or drive in outlets
1993	June: Grand Met/ Wimpy agreement expires
	McDonalds has around 500 outlets
1994	Wimpy has 240 outlets, all eat-in
end 1995	Burger King has approx. 300 outlets McDonalds has over 600 outlets
May 1996	Wimpy has 272 outlets
	McDonalds and Burger King each opening around 70 restaurants per year
2001	Wimpy still has less than 300 outlets, McDonalds over 1000 outlets.

Table 2
Descriptive statistics of local authority districts

Variable	Mean	Standard Deviation	Minimum	Maximum
Area (square km)	493	717	15	6497
Population (thousands)	124.0	94.956	11	1017
Youth (%)	14.0	1.127	7.0	17.0
Pensioners (%)	19.0	3.452	12.0	35.0
Council Tax (£)	419.761	163.724	0	963
Wage (£000)	13.985	1.801	1.085	17.208
Unemployment (%)	6.0	2.386	1.0	26.0

Table 3A
Sample characteristics

District ref #	Market area sq. km.	Entry order	1st/2nd same chain dist. metres	First mb pair dist. metres
4	204	mmb	2445	2690
26	112	mmb	475	87
50	367	mmmb	8934	971
53	410	mmb	11165	11177
59	78	mmmmmb	2571	122
94	75	mmmb	1544	125
100	333	mmb	1917	147
117	43	mmb	1252	1114
180	315	mmb	3597	11536
181	32	mmb	1609	5468
231	80	bbm	422	185
275	290	mmb	3617	180
283	93	mmb	1325	612
291	97	mmmb	5471	680
292	98	mmmmb	3877	3877
296	69	mmb	1453	45
309	160	mmb	5790	5886
314	199	mmmb	9541	260
315	137	mmb	2300	2307
316	35	mmmb	1876	299
323	142	mmb	2655	4893
331	153	mmmmmb	21717	21716
333	159	mmmb	3477	3548
370	246	mmb	5304	160
422	235	mmb	3293	3374
437	81	mmmb	3852	6468
438	48	mmmb	4614	5419
444	110	mmmmb	6326	4482
448	38	mmmb	3603	3317
451	38	mmmb	3021	302
453	56	mmmb	656	420
455	29	mmmmb	2931	3187
456	43	mmb	294	473

Table 3B
Sample characteristics

District ref #	Market area sq. km.	Entry order	1st/2nd same chain dist. metres	First mb pair dist. metres
12	197	mbm	2556	152
49	283	mbm	2544	161
55	333	mbm	1592	436
65	130	mbm	1108	1975
96	41	bmb	780	410
107	39	mbm	1776	148
111	39	mbm	1506	178
116	477	mbm	1388	311
128	309	mbm	4778	113
148	42	mmb/mbm	331	63
166	212	mbm	3662	440
178	309	mbm	9236	253
219	375	mbm	2014	112
248	41	mmb/mbm	3422	1086
297	448	mbm	1689	138
306	99	mmb/mbm	5009	241
365	120	mbm	3161	275
410	285	bmb	2748	1772
435	87	mmb/mbm	381	81
46	29	mbb	218	141
168	98	bmm	8593	242
310	97	mbb	1021	790
385	184	mbb	640	324
419	307	bmm	3092	3232
Mean	161.16		3441.61	2080.72
Median	112.00		2571.29	419.64

Table 4
Distances across the first three outlets where the second has a different identity from the first

Distance	1st/2nd same chain dist. metres	First mb pair dist. metres
mean	2615	439
s.d.	2080	556
median	2014	241

Table 5
Descriptive statistics on minimum distances, 1994

	Sample 1			Sample 2			Sample 3		
Metres	**MP**	**MB**	**BP**	**MK**	**MB**	**KB**	**MW**	**BW**	**MB**
# of districts	**36**	**36**	**36**	**19**	**19**	**19**	**20**	**20**	**20**
Median	181.69	186.43	299.00	189.84	440.24	405.29	234.19	305.90	181.55
mean	844.61	598.32	2199.32	1362.72	1622.52	2242.73	705.80	2900.58	1511.12
s.d.	1847.24	933.11	4283.70	2169.34	2794.23	3419.24	1392.98	5539.15	3032.42

Proportion	**MP**	**MB**	**BP**	**MK**	**KB**	**MW**	**BW**	**MM**
# of districts	**36**	**57**	**36**	**19**	**19**	**20**	**20**	**51**
median	0.014	0.022	0.024	0.017	0.034	0.017	0.021	0.190
mean	0.076	0.078	0.177	0.141	0.174	0.074	0.242	0.218
s.d.	0.164	0.154	0.324	0.243	0.238	0.160	0.413	0.154

Note: M = McD , P = Pizza Hut, B = BK, K = KFC, W = Wimpy. Source: see text.

Table 6
Regression results to explain distance between McD and BK first outlets

Variable	(1)	(2)	(3)	(4)
Time	-7409**	-7409**	-10000**	-7237**
	(3499)	(3499)	(4465)	(3403)
	[-19227, -1126]		[-28076, -3606]	
Rank	-4585**	-2054	-3831**	-44.79*
	(1904)	(1272)	(1508)	(22.96)
	[-9891, -1104]		[-8902, -1040]	
Rank sq.	328.9*	289.2	145.2	.155*
	(184.0)	(178.4)	(175.7)	(.083)
	[-18.43, 950.1]		[-204.1, 882.6]	
McD distance	.876***	.876***	.861***	.887
	(.155)	(.155)	(.165)	(.158)
	[.098, 1.049]		[.139, 1.041]	
# McDs	-218.9	-218.9	-20.27	-168.9
	(335.4)	335.4	(275.0)	(341.3)
	[-1185, 432.2]		[342.1, 910.9]	
Constant	23510**	2736	27350**	1825
	(10590)	(1873)	(11440)	(1359)
	[4076, 56493]		[6112, 16929]	
Rank variable	Increases by 1 after every 50 outlets	Increases by 1 after every 50 outlets	Increases by 1 after every 50 outlets	Straight rank
Time variable	Log of years between 1st McD entry and 1990	Same, orthonormalized	Same, capped at 10 years	Same, orthonormalized
Nobs.	37	37	37	37
R-sq.	0.624	0.624	0.646	0.636
Breush-Pagan	0.269	0.269	0.138	0.257
F-test	0.000	0.000	0.000	0.000

Notes: Reported numbers are coefficient, standard error, and bootstrapped 95% bias corrected confidence intervals in square brackets. ***, **, and * denote significance at 1, 5, and 10 per cent levels. Breusch-Pagan is the p-value of a B-P test of homoskedasticity. F-test is the p-value of an F-test of the joint significance of all RHS variables.

Table 7
Regression results to explain distance between McD and BK first outlets

Variable	(1)	(2)	(3)	(4)
Time	-11760	-17260**	-7785**	-6138
	(10630)	(8534)	(3830)	(3675)
	[-58594, 19173]	[-49221, 10214]		
Time sq.	1338	2312	-74600**	-87490***
	(3029)	(2384)	(34670)	(32320)
	[-8673, 10606]	[-8727, 9103]		
Rank	-3804	-4877*	-1937	-55.92**
	(3011)	(2432)	(1517)	(26.81)
	[-12941, 3032]	[-12343, 305.28]		
Rank sq.	263.0	276.9	370.3*	.243**
	(350.8)	(302.7)	(210.9)	(.093)
	[-505.6, 1442]	[-352.3, 1136]		
McD distance	.866***	.824***	.899***	.917***
	(.150)	(.125)	(.138)	(.129)
	[-.039, 1.109]	[322, 1.011]		
# McDs	509.7	366.4	707.0	843.1
	(600.3)	(535.9)	(556.0)	(518.4)
	[-544.7, 2288]	-427.6, 1400]		
Population	-7.854	-	-9.487	-10.48
	(8.170)		(7.487)	(6.963)
	[-31.70, 10.06]			
Area	-1971	-	-3055	-5146
	(6108)		(5607)	(5224)
	[-16859, 27556]			
Youth	1582**	1461***	1976***	1930
	(648.3)	(453.4)	(574.6)	(537.6)
	[396.7, 3080.8]	[452.2, 2341]		
Pension	712.1**	631.9**	794.6***	704.3
	(285.8)	(244.7)	(259.0)	(243.8)
	[118.4, 1744.6]	[152.3, 1617.1]		
London	1074	-	2833	1489
	(2348)		(2063)	(1991)
	[-4337, 7255]			
McD nbors	40.66	-	122.0	110.5
	(124.1)		(116.0)	(105.9)
	[-283.9, 335.3]			
BK nbors	98.00	-	-248.3	-68.97
	(391.0)		(352.8)	(327.3)
	[-758.0, 888.4]			
Constant	-8854	3030	-38820***	-36450
	(17100)	(12450)	(12240)	(11400)
	[-65818, 35770]	[-26683, 33486]		
Rank	Increases by 1	Increases by 1	Increases by 1	Straight rank

variable	after every 50 outlets	after every 50 outlets	after every 50 outlets	
Time variable	Log of years between 1st McD entry and 1990	Same	Same, orthonormalized	Same, orthonormalized
Nobs.	37	37	37	37
R-sq.	0.766	0.739	0.804	0.830
F-test I	0.835	-	-	-
F-test II	0.907	-	-	-
F-test III	0.000	0.000	0.000	0.000
Breusch-Pagan	0.343	0.377	0.917	0.923

Notes: Reported numbers are coefficient, standard error, and bootstrapped 95% bias corrected confidence intervals in square brackets. ***, **, and * denote significance at 1, 5, and 10 per cent levels. F-test I is the p-value of an F-test on the joint significance on all the market controls (population, area, youth, pension, London, mcdboro, bkboro). F-test II is similarly a joint test on all the market controls that have insignificant coefficients in column (1). F-test III is the p-value of a joint significance test on all RHS variables.

Appendix

A product differentiation framework for the analysis of micro-location

Consider a model where

- Competition is purely in location, not price (implicitly, price is equal across players)
- Profits are proportional to the market served
- There are only two strategic players
- Each player produces the same product
- Locations once chosen are sunk
- Players can choose more than one location
- Consumers prefer near outlets to those further away
- Location is sequential with foresight
- The space is finite (say a plane of diameter 1) with constant density of consumers.

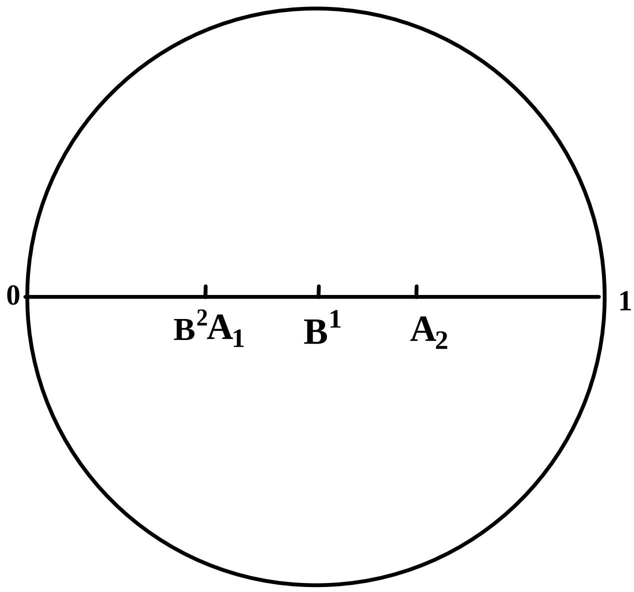
In such a model, the firms' optimal choice of location is such as to minimize the average distance between consumers and the outlet(s). Trivially, if there is only "room" for one outlet, that outlet will locate centrally in the space, as a tiebreaker.

If there will only ever be two outlets, one from each player, they will share the market equally. One possible equilibrium has them located close to each other in the center. Moving away from the center carries with it the danger that the second-mover will take more than half the market. It follows that in neither of these cases are we able to test a location model against a model of learning, since they lead to the same prediction.

However, in cases where there is room for three or more outlets, it is possible to show that predictions of the two models differ. The learning story would have the first outlet of a rival relatively close to the *first* outlet of the first firm. Prescott and Visscher (1977, henceforth PV) devised an algorithm for sequential location along a line, assuming location with foresight, under the assumption that each player has only one location and that there is room for three firms. It involves a backward induction process. However, since we have two firms, with one having two locations, and since we consider a plane not a line, we need to modify their process. In PV, the first firm locates at ¼, the second at ¾ and the third at ½. Thereby the first firm obtains profits of 3/8, as does the second, whilst the third firm obtains ¼. The player with two outlets will want to ensure itself at least as much profit as it would have obtained operating them independently.

There are two cases involving three outlets, and we denote them AAB and ABA. The two players are A and B, and the order in the list determines the order of moves.[29] The AAB case is pictured below. Two possible locations for B are presented (a third is a symmetrical location to the right of A_2).

[29] Note that, in the P&V model, the profit for A in the first case is ¾ whilst B earns ¼. In the second case, under this assumption, A earns 5/8 and B earns 3/8.



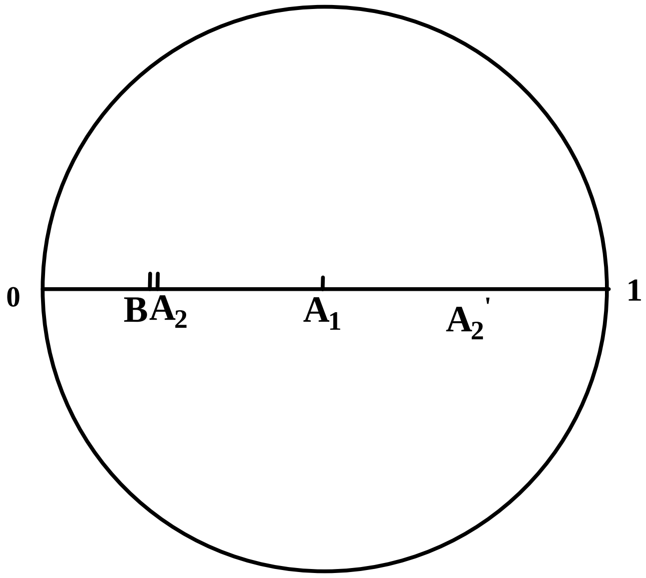
To analyze this case, note that A has the first two moves and B has the last move. Thus this can be collapsed into a two-stage game. A's two outlets may be represented as being on a chord. A's problem is to locate so as to split the total area in such a way that B's market is minimized. Assume for the moment that A locates at two points on a diameter. The choice of these points is such as to render B indifferent between locating just to the outside of one of A's outlets and locating in the center. That is, A's locations satisfy the criterion that half the market between them is equal to the market to the outer side of each. A obtains a total of ¾ of the market and B obtains ¼. B is indifferent between locating at B^1, at B^2, or just to the right of A_2. Of these possibilities, location at B^1 is least vulnerable to minor perturbations of the assumptions. In the first of these cases, calculation establishes that A_1 is located at approximately point 0.3 on line [0,1], B is located at 0.5 and A_2 at 0.7. More generally, the equilibrium prediction is that $A_1B=0.5A_1A_2$, *or* that (A_1 or A_2) and B locate very close, whilst the larger distance (B to one A) is the same as distance between the As. This second prediction is at least partially in line with what would be expected from a learning story. If there were to be a subsequent A entry, the position B^1 would be the more likely, since in the case of location B^2, a further A entry would remove B's market entirely.

To argue that this exhausts the list of equilibria, note that for A, locating one outlet in the center would be foolish, since B would then, by locating just to one side in the final move, obtain half the total area. Locating asymmetrically is unlikely to be optimal for A since it provides an asymmetric distribution of the total area that B can benefit from. Given that the A outlets will be some distance apart, B can never do worse than by locating equidistant between the two A branches on the chord that joins them and may be able to do better (for example by positioning itself on the perpendicular from the chord on which they lie at an equal distance from the center as is that chord). Thus locating on the chord that is the diameter is better for A than locating on an alternative chord.

The predictions survive an extension to the case where density is non-uniform but symmetric and single-peaked in the center. Clearly, A's two outlets now locate nearer to the center than is represented in the figure above, but the *relative* distances between the three outlets do not change.

The framework can be modified to cases where the location pattern is AAAB, AAAAB, etc. In the first of these, A will locate its three outlets in a triangular formation around the center, again bearing the same criteria in mind, namely of cutting B off from the maximum amount of area. In the second, the formation will be a square, etc. The predictions, appropriately modified, remain as before.

The second category, ABA, is pictured below.



Here, A locates first in such a way as to make B indifferent between which side of A it goes. In other words, A locates in the center. Then B locates so as to make A indifferent between which side of B it goes, whereupon A locates immediately to one side or the other. Note that since A_1 is in the center, all players can be represented along a diameter. B locates with 1/6 of the area to its outer side, and 1/3 between it and A_1, in pursuit of indifference in the location of A_2. Thus A obtains 5/6 of the market and B, 1/6.

However, this pattern is vulnerable to the possibility of any further entry. In particular, there is no benefit for A to moving very close to one side of B's existing outlet, because there is always the chance B will come in afterwards and surround A's outlet. If this is a consideration, a better location for A's second outlet is to the other side of its first, as shown by A_2', so that B becomes indifferent between several possible positions in regard to its second outlet. In either case, the equilibrium prediction is that distance A_1A_2 is less than or equal to distance A_1B (note that the locations of A_1 and A_2 cannot be reversed). Again this prediction appears rather robust to modifications of the framework in terms of a non-uniform but smooth and single-peaked density and in terms of possible additional outlets.

The prediction from a strategic location model in the ABA case is substantially at variance with what would be predicted from a vicarious learning model. Thus availability of such cases will provide a strong discriminator between the two models.

Of course one may argue that the players are not producing the same products as each other. Therefore, considerations of existing rival outlet locations may not play as big a part as implied by the modeling framework developed here. However, if this is so, we would nevertheless expect that considerations of rivalry would play a bigger part in the case of McD versus BK than in the location of other fast food outlets relative to McD.