Fast Food: The Early Years*

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Abstract

We examine the development of the outlets of a major fast food chain in the UK, from their inauguration in 1974 until 1990, when the industry structure changed somewhat. The chain effectively introduced counter-service burgers to most of the UK. Locational diffusion across local authority district markets is explained by means of the characteristics of the areas in which the outlets are sited. Both first and second entry are examined. We find in both cases that the hazard of entry is positively influenced by market size and population density and negatively by distance from company headquarters.

Keywords: Fast food; Diffusion; Regional economic activity; Entry

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Introduction

One of the pervasive phenomena of the twentieth century is the spread of chain stores. In the latter part of the century, a prominent element of this is the spread of chain fast food outlets. These have enjoyed remarkable success in expansion, so that fast food chains now constitute a significant industry. For instance in the UK, restaurants employ more people than do, for example, agricultural services in their entirety or the textile industry. Our purpose in this paper is to examine the spread of a paradigmatic examp1e. In doing so, we argue, we are casting light upon the phenomenon of the growth and development of chain stores generally.

In this paper, we examine the growth of a particular fast food company, McDonalds (McD) in the counter service burger market. Our investigation, for reasons we explain in more detail later, centres on the growth from its inception in the UK until a period 17 years later when it first faced significant competition, thus on a phase during which it was without major competitors. A shorter subsequent phase, during which we examine a duopoly, is the subject of an earlier paper (Toivanen and Waterson, 2001). The company in question may justifiably lay claim to having innovated a method of food production in the UK. Therefore, at one level, we are examining the spread of an innovation. However, our focus is on the more specific issue of uncovering the variables that explain the duration of time before which an outlet opens in a particular market location[1]. There have been several such studies in the literature on the diffusion of innovations. However, our study is the first, to our knowledge, which uses geographical characteristics of the market in the explanation and is unusual in its focus on a service activity. Indeed, we find that "geography matters" to the question of how long it takes before an outlet opens, a finding that has implications we draw out in the concluding sections.

Modelling the duration of time before a client adopts an innovation is quite a popular activity, at least so far as process innovation is concerned. Indeed, it is normal for innovations to diffuse over a substantial period of time. Examples of such studies include Hannan and McDowell (1984), Rose and Joskow (1990) and Karshenas and Stoneman (1993). Hannan and McDowell (1984) use a duration model to investigate the decision by banks to adopt automatic teller machines (ATMs). They assume that a firm is more likely to adopt an ATM,

[1] A legitimate question arises as to whether it would be more straightforward to ask the company themselves what factors influenced opening policy. We are not adopting this direct approach because we feel it is unlikely the company will have a corporate memory extending back almost 30 years, because they may not wish to articulate their policy to outsiders and, most importantly, because the tools used in the years we study may well have been implicit rather than explicit- certainly their approach towards opening outlets became more sophisticated only in the mid 1990s.

the greater the profit differential between adopting and not adopting. In turn, they identify a number of firm and market characteristics that will help determine profitability; these include the wage rate in the market, market growth, and firm size. Rose and Joskow (1990) use data on coal-fired steam-electric generating technology to investigate the effect of firm size and ownership on technology diffusion. They acknowledge the fact that firm size has been identified as an important determinant of technology adoption in other empirical studies, but suggest that its role has been overstated. In choosing to analyse the electric utility industry at that time, any competitive and market structure features are eliminated. Each firm acts as a monopoly, and is subject to some kind of regulation depending upon whether the utility is investor or government owned. The study investigates the parts played by firm size, factor cost differences, ownership structure and time in the diffusion process. Karshenas and Stoneman (1993) construct a general duration model of technology diffusion that combines the main elements present in the competing theories of process-technology diffusion, namely the epidemic, rank, stock and order effects discussed above. Their model is applied to data on the diffusion of computer numerically controlled machine tools (CNC) in the UK engineering industry, and they investigate whether any of the above-mentioned effects play a part in the diffusion process. A hazard-rate approach is undertaken, with the conditional probability that a firm adopts a new technology in a given time being dependent upon variables from the rank, stock, order and epidemic effects models (although only the first and last of these prove significant). Overall, the key element all studies identify as being important for adoption time is the size of the purchaser market.

However, another aspect of the literature that provides a strong influence on our econometric work is not about diffusion at all; rather it concerns fertility. Heckman and Walker (1990) concern themselves with fertility dynamics. They estimate a reduced-form neo-classical model that brings together various factors, such as childlessness and inter-birth intervals, that relate to life-cycle fertility. They attempt to discover whether these factors are sensitive to male income and female wages. Previous studies indicate a negative relationship between a woman's education and the number of children she has (completed fertility), with a woman's education here being used as a proxy for her wage. The interesting aspect of this study is that it examines duration before first and second child. In a similar way we examine duration before first and before second entry into a market, something that has not been done previously.

In order to investigate duration models of diffusion adequately, Karshenas and Stoneman

(1993, p.513) state that the project dataset employed should satisfy a particular set of criteria: "[T]he ideal would be a dataset with complete life histories of the population of potential adopters, as well as the characteristics of a well-defined new technology over a sufficiently long period beginning with the appearance of the technology in the market." Essentially, this is what we have. In the current study, the potential adopters of the new technology, that is a McDonalds outlet, are the Local Authority Districts within the UK. Data relating to McDonalds is available for the full 1974-1990 period, commencing with outlet data for the first McDonalds which opened in Greenwich in October 1974. Local Authority data is also available for the period of study, and therefore the requirements set out in the above statement are fully met in our data set.

Our plan for the remainder of the paper is as follows. We first discuss the characteristics of the market we study, then develop our economic model of entry, explain our econometric method and discuss our results. We conclude with some implications of our findings.

Characteristics of the Market and the Data

We argue that the fast food counter-service burger market is a well-defined (and dominant) segment of the general fast food market. Counter service is significantly different from table service, because of the very different amounts of time involved. Over the period in question (from 1974 to 1990), counter service burger sales grew significantly in the UK at the expense of earlier fast food activities, primarily fish and chips. However, the nature of the outlets is very different. Fish and chip sales were (and are) concentrated very much at particular established times of day, early lunchtime and evening, often very late evening, and do not normally operate outside those times. Nor, for historical reasons, do they operate on Sundays. By contrast, burger outlets open from around 9am and supply continually until mid or late evening. Fish and chip outlets seldom incorporate seating. They employ batch rather than continuous production methods.

Geographically, we define the local market to be equivalent to the local authority district. People in the UK do not travel far to satisfy their fast food needs, in part because much of the custom arrives on foot. The local authority district is a convenient level at which to perform the analysis, since comparable data on key variables are available for long periods, something required for this analysis[2]. Moreover, it is of significance that they differ considerably in their

[2] By lucky chance, the last major re-organisation of the structure of districts was completed in 1974, since which all changes have been minor. Basic demographic data is available since 1974. To these we add data on distance

core characteristics such as size. Table 1 shows some key features of the market, illustrating this diversity in terms of factors such as population and wages. Therefore, we may expect that some markets are considerably more attractive prospects to enter than others and hence will be entered sooner. Our estimation strategy relies on the position that the characteristics of the innovator remain essentially constant, whilst the characteristics of the units of observation vary considerably, so that we may hope to identify precisely the key elements of districts that influence the decision process in determining duration before entry.

The market so defined is very amenable to study of innovative entry. Table 2 illustrates some key features of the market as a whole. Note that in fact the first counter service burger outlets were introduced to the UK by the Wimpy chain. However, Wimpy never strongly embraced the counter service concept, preferring instead to concentrate on table service, and indeed in a major industry reorganisation in 1990, abandoned counter service altogether for many years. It is also not a chain that has ever experienced strong growth. By contrast, the growth of counter service burger outlets in the hands of McDonalds has been remarkable in extent, so that we have plenty of activity to observe, and remarkable also in that virtually no closures have taken place- we are observing entry without exit. Thus we are observing a successful innovation, embraced wholeheartedly by the company. It went from 0 to 381 outlets in 17 years, with but a single confirmed exit (which we ignore on de minimis grounds). We finish our main exploration of the data in 1990, since in 1991 Burger King becomes a credible second force in the industry for the first time. Prior to this, McDonalds had no powerful competitors. However, we intend to re-examine this later period using the same maintained assumption to check the nature of the impact upon the McDonalds expansion process. One other feature worthy of note: In the UK, McDonalds largely developed as a management-operated company, not through franchise operation; note that franchising did not start until 12 years had elapsed since the first entry. Moreover, it is a highly centralised company, whose franchisees do not make independent decisions about location of outlets. Therefore, we consider franchised and managed outlets together.

Figure 1 shows that, viewed as an innovation, McDonalds' spread across local authority districts does indeed take on the characteristic "S"-shaped diffusion pattern observed in so many previous studies. Similar figures drawn for second and for third entry into a district do not exhibit a slackening of growth in the later periods, indicating a less mature degree of fill-

of the district from McDonalds Head Office, in miles by road- see later.

in, as might be expected. However, our purpose is not to demonstrate that an S-shape exists, but rather to examine the much more sophisticated issue of explaining duration before entry into particular districts.

In this context, the firm McDonalds represents the supply side in this study, and it is assumed to be the decision-making unit, choosing where to supply each subsequent McDonalds outlet. This differs from most of the process-technology literature discussed in the Introduction which assumes the demander(s) of the technology to be the decision maker(s). McDonalds outlet data was obtained direct from the Company's UK head office. It embodies information on store location, including the postcode and telephone number, store type (owned or franchised, drive through or not), exact opening date and store number[3]. There are 381 outlets included in the main estimation dataset and each is matched to a Local Authority District using either a Midas "Postzon" package based on UK postcodes, or the Bartholomew Postcode Atlas of Great Britain and Northern Ireland, a Royal Mail publication.

The Local Authority Districts are physical places and they represent the demand side in this study. This is the smallest unit of local government in the UK, and generally consists of a city, or a town with some hinterland, or a largely rural area. The estimation dataset relates to 455 districts, since districts in Northern Ireland and most island-based districts (the Scilly Isles, Orkney, Shetland and the Western Isles) are not included in this study. There are 17 consistent annual observations for each of the 455 districts within the estimation sample, namely, geographical area, population, the distance from the district to the McDonalds headquarters, and the number of McDonalds outlets in neighbouring districts. The geographical area and population data mainly come from Regional Trends (formerly Regional Statistics)[4]. In certain cases, the definition of the districts has changed in minor ways during the 1974-1990 period[5]. Population and area data for the districts in question is transformed to be consistent with the 1990 definition of the districts. In order to construct the revised population data, the percentage of an area that is to be added to another is multiplied by the former area's population figure to give the amount by which the latter's population has to increase. Consequently, the former's population is reduced by the same amount.

[3] The store number provides a very useful cross-check on opening data and enables us to verify exit.
[4] A full list of district-level data is not available for all years, and therefore various Regional Trends sources (Office of Population Censuses and Surveys and Annual Report – Registrar General Scotland) are used in addition.
[5] We use geographical area data to check consistency in local authority definition over time, with any discrepancy >1% investigated.

The distance from each district to the McDonalds headquarters in Finchley is calculated by assuming that the location of the district is at the named place in the case of a district based on a particular name e.g. Coventry in the case of Coventry district. In some cases, the district's name does not correspond to a name on a map, and in this case, the location of the main council offices is taken to be the place. Distance is then calculated using the Automobile Association product 'A to B'; a commercial software product designed to help people plan their journeys.

For each year of study in each district, the number of pre-existing McDonalds' in neighbouring local authority districts is calculated. Neighbouring districts are identified by using maps from the Office for National Statistics. A neighbouring district is defined as any district connected continuously by more than a single point to the district in question.

Using the panel of market-level data described above, *the hazard of McDonalds opening an outlet in market j in year t* is investigated. We view the prime question as being whether or not an outlet is opened, rather than whether a larger or smaller outlet is opened, which is a second-order decision. The question of whether diffusion is regional in nature is also investigated so that the question of whether a firm opens outlets around where it already has a presence can be assessed. Also, the time to first and second entry within a district is analysed, allowing differences between first and second entries to emerge. Time starts running from January 1974 where the first entries are concerned, whereas time for the second entries starts running from the opening of the first outlet. Hence, second and higher outlets have different calendar times.

Modelling entry

Our aim is to explain the hazard of McDonalds opening an outlet in market j in year t. Our approach is to say that McDonalds in the UK decides annually to search for and select profitable locations to enter in that year, choosing first to develop the (ex ante) most profitable. We know that exploring and investing in new sites is a time-consuming activity and development of the chain takes many years. There are several possible explanations for this. Either there may be a limit on how many outlets can be accurately assessed per year, for institutional reasons, or development costs may fall over time as a result of innovations and economies in the process[6], or demand may rise over time as consumers become more used to

[6] There is some indirect evidence on this coming from a presentation by McDonalds executives to a conference at CIFE, Stanford in 1997. The emphasis in this presentation was on a new approach to developing outlets that

buying the product, so rendering increasing numbers of sites viable. Whichever of these is the case, it will become profitable over time to open outlets in previously sub-marginal areas. Thus at any given point in time, whichever of these processes is in operation, choices are made about the next sites to open. What are the likely main influences on this?

The most important factor potentially involved in explaining duration before entry (or the hazard of entry, which is what we actually examine) is market size, of which the proximate determinant is population- the greater is population of potential consumers, the greater the hazard of entry. Given market size, we may argue, the more densely populated is the market the greater the hazard, so that the larger the geographic area covered by the local authority, ceteris paribus, the lower the hazard. But in both cases these are unlikely to be linear relationships- e.g. doubling market size is unlikely to halve the time before an outlet opens in that district. Given population, demographics may also have an influence.

Distance from Head Office of McDonalds is also likely to have an influence, either in terms of demand or, perhaps more plausibly, in terms of costs. The further away is the district from head office, the greater the costs of surveying potential sites and arranging construction, the more likely are tastes to be unknown or undeveloped and the more costly to monitor and to service the outlet with inputs. Again these factors are likely to have a non-linear impact on the hazard and we take this into account in our empirical formulation by using each variable and its square as explanatory variables. Neighbouring outlets present a more difficult problem. In developing an area, if there are already outlets in neighbouring areas, we conjecture it makes it more likely that an outlet will open *ceteris paribus*, since more can be serviced at once- there are economies of density in examining locations and in servicing sites. (On the other hand, it is possible that neighbouring area outlets will "spoil" a market if they are too close.) If indeed these factors are important, then "geography matters"- the development of the chain will be conditioned by the fact of where it started. However, the number of neighbours is arguably not something that should be entered directly, because it is endogenous to the process. Hence, instruments should be employed.

These are basic demand side factors. In addition, there are cost side factors, potentially. For example, areas of greater demand may also have greater rents, or higher building costs,

reduced the time and money spent on developing outlets through linking the work of architects, contractors, etc much more closely through use of common technology platforms. This approach was being introduced as a concept in the US starting in 1993.

leading to more costly construction. Wages may also be higher in some places than others. Some such factors will be included in later versions of the paper.

We consider second entry to be subject to the same basic determining factors as is first entry, although we have very much less in terms of previous work to guide us in this area, since it has not been considered within the diffusion literature. Thus, for example, the larger the population, the earlier a second outlet will be opened in a district, ceteris paribus. Hence, our basic estimating equation in both cases is along the following lines:

Hazard = f(pop., popsq, area, areasq, dist., distsq, neighbour variables) (1)

Econometric Method

Our objective is to model the conditional probability that a McDonalds outlet will enter a particular district, conditional upon one not having entered up to that point in time. Thus we are modelling the hazard function. We approach estimation of the time duration (hazard) to first entry using an essentially non-parametric baseline hazard estimation procedure. On top of the basic non-parametric structure, we place a parametric explanatory element using the variables listed in (1) above.

Although the underlying process can be thought of as occurring in continuous time, the data are not observed in that form. The survival times have been grouped into discrete intervals of time (years) so that observed spell lengths are summarised using positive integers[7]. For the purpose of this study, the observations on the transition process are therefore assumed to occur in discrete time. The discrete-time hazard can be thought of as a conditional probability rather than a rate and is therefore bounded between 0 and 1. We use the Prentice-Gloeckler (1978) model incorporating a gamma mixture distribution to summarise unobserved heterogeneity, as proposed by Meyer (1990). This is a proportional-hazards model, also known as a log-relative hazards model, that implies that absolute differences in explanatory variables lead to proportionate differences in the hazard rate at each point in time. Explanatory variables included in the model are either fixed over time (area and distance) or are time varying (population and neighbours). The time-varying covariates are assumed to vary between time intervals but to be constant within each of them.

[7] All indications are that planning is based upon a one-year cycle.

The discrete-time model we consider can be obtained by grouping time in the continuous-time proportional-hazards model. Each district $i = 1,\ldots n$, faces the possibility that a McDonalds outlet will open within its border at time $t = 0$. The continuous-time hazard function for district i at time $t > 0$ takes on the proportional hazards form

$$\lambda\left(t; x_i\left(t\right); u_i\right) = \lambda_0\left(t\right) u_i \exp\left\{x_i\left(t\right)'\beta\right\} \tag{2}$$

where $\lambda_0(t)$ is the baseline hazard at time t, u is a gamma distributed random variable, exp(.) is the exponential function, $x_i(t)$ is a vector of covariates summarising observed differences between individuals at t and β is a vector of parameters to be estimated. The baseline hazard is assumed to take on a non-parametric form that allows differential effects between years. This strategy focuses on estimation of the regression coefficients β leaving the underlying baseline hazard describing the data completely unspecified so that it may be linear or sinusoidal, for example.

Failure to control for any unobserved or omitted district-specific effects that may affect the hazard function will lead to inconsistent parameter estimators (Lancaster, 1990). Unobserved or omitted heterogeneity between districts is addressed in the above model by including a gamma distributed random variable u, with unit mean and constant variance σ^2. A crucial assumption is that u is distributed independently of x and t.
The associated continuous-time survivor function is

$$S\left(t; x_i\left(t\right); u_i\right) = \exp\left\{-u_i \exp\left(x_i\left(t\right)'\beta\right) H\left(t\right)\right\} \tag{3}$$

where $H\left(t\right) = \int_0^t \lambda_0\left(t\right) dt$ is the integrated baseline hazard

The underlying continuous durations are, as mentioned above, only observed in disjoint time intervals $[0=a_0, a_1)$, $[a_1, a_2)$, $[a_2, a_3)$,…,$[a_{k-1}, a_k=\infty)$. Given that a proportional-hazards model is assumed, the discrete-time survivor function for the jth interval has the same form as (3),

$$S\left(a_j; x_i\left(t\right); u_i\right) = \exp\left\{-u_i \exp\left(x_i\left(t\right)'\beta\right)\delta_j\right\} \tag{4}$$

where $\delta_j = H\left(t\right)$ for $j = 1,\ldots,k$

and the discrete-time hazard in the jth interval is

$$h_j\left(x_{ij};u_i\right)=1-\exp\left\{-u_i\exp\left(x_{ij}'b\right)g_j\right\} \qquad (5)$$

where $g_j=\int_{a_{j-1}}^{a_j} l_0(t)\,dt$

All intervals are assumed to be of unit length, and the recorded duration for each district i corresponds to the interval $[t_{i-1}, t_i)$. Those districts having a McDonalds entry during the interval are identified using the censoring indicator c_i = 1, and those that remain in the state are identified using c_i = 0. The latter have no entry during the interval and are right-censored data in the study. Given these assumptions, the log-likelihood function for the sample of N districts is

$$\text{LogL}=\sum_{i=1}^{N}\log\left\{\left(1-c_i\right)A_i+B_i\right\} \qquad (6)$$

where

$$A_i=\left[1+s^2\sum_{j=1}^{t_i}\exp\left[x_{ij}'b+q(j)\right]\right]^{-s^{-2}}$$

and

$$B_i=\left[1+s^2\sum_{j=1}^{t_i-1}\exp\left[x_{ij}'b+q(j)\right]\right]^{-s^{-2}}-A_i \qquad \text{if } t_i>1$$

or

$$B_i=1-A_i \qquad \text{if } t_i=1$$

where $q(j)$ is a function describing duration dependence in the hazard rate, in this case a non-parametric baseline hazard specification is assumed.

The above modelling framework is used in estimation on first -entry data. A very similar approach is adopted in respect of the second entry of an outlet, since we assume this to be affected by the same underlying factors that influence the hazard of first entry. Of course, in this case time is measured from the time of first entry. In estimation, we grouped the data in order that no year remained in which there was no first (second) entry. Thus in the first-entry case, year 1 in which only the initial outlet was introduced was grouped with year 2. In the case of second entries, years 11 and 12 were combined, as were years 13-16[8]. All 455 districts as defined above are included for the first-entry model, whereas those districts with no entries by the end of the sample period are excluded for the second-entry model. Of the 2

[8] There are of course only 16, not 17, years of observations as far as second entries are concerned.

models estimated, only first-entry results show evidence of unobservables. First-entry results reported are therefore from a model including unobservables (as shown above), while second-entry results are from a model without unobservables; the limiting case as σ^2 tends towards zero. This is explainable since the second entries can only take place in that subset of districts in which first entries have already occurred, which is relatively homogeneous compared with the population of districts.

Results

Table 3 shows the results of the estimation of the first entry hazard. From these we see that all the explanatory variables have a significant impact on the hazard of first entry; in each case the effect is non-linear. Population has an increasing impact on the hazard, tailing off as population increases, but still comfortably positive at the mean. Distance, in an opposite manner, has an initial negative influence on hazard, but the influence tails off as distance increases. At the mean, it is still negative. Area of the district has an essentially similar impact to distance, with the implication being that with population held constant, as population density increases, the hazard increases, but at a decreasing rate. All these variables have a statistically very significant impact upon the hazard. In addition, we experimented with various forms of the neighbour variables in combination. The version here incorporates three such variables in total. The overall impact is strongly positive, indicating as expected that the presence of outlets in neighbouring districts raises the hazard of an outlet being introduced into a particular district, particularly in more distant locations. Of course, it should be recalled that the neighbours variable is endogenous and therefore violates the maintained assumptions of the statistical model. This finding should therefore be reconfirmed using appropriate instruments, something we intend to do in later versions of the paper.

The basic pattern of the underlying estimated baseline hazard is that early years (up to around year 8) have significantly negative dummy values, at decreasing rates over time, but starting at high negative values. The later years (10 to 16) have significantly positive values, but at lower coefficient values than the early negative rates. Comparisons with the raw entry rate, depicted in Figure 2 are interesting. As can be seen in the figure, the hazard increases rapidly after about the first seven years of presence, then shows signs of tailing off towards the end of the period of observation, in a way broadly consistent with the estimated values and with a sinusoidal pattern commonly viewed as characteristic of such data.

We have less success in explaining the hazard of second entry, as can be seen from Table 4. Of the variables that we employ, only population, which has the expected positive effect, and neighbours (again the expected positive effect, although naturally subject to caveats, as before, regarding endogeneity) are significant. Population density and distance from head office appear not to matter for this decision.

Concluding Remarks

Our results show that the basic structure of explanatory variables we have developed is capable of providing a very good explanation of the underlying elements of the hazard of entry of a McDonalds fast food outlet into a district of the UK. One implication worthy of note is the extent to which "geography matters" to the result- it matters not just what the characteristics of the district are, but also where it is in relation to head office. In this respect, we may conjecture that if McDonalds had started in Glasgow, or Birmingham or Manchester say, rather than Greenwich in London, the overall pattern of development would have been very different. It would be interesting indeed if it transpires that this result is true more generally, something we intend to examine in later papers.

Furthermore, the findings regarding neighbouring outlets, whilst obviously subject to caveats, are also intriguing, because they reinforce the influence of geography on the outcome. They also imply that chance regarding the location of early outlets (for a given distance from head office, and given population etc.) can have an influence on the spread of a chain. For example, it would seem that if a chain develops first in a westerly direction, then this westerly bias is likely to continue. This is a fascinating possibility, which obviously requires further investigation.

Table 1
Descriptive Statistics on Local Authority Districts

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

Table 2
Key Dates in the UK History of Burger Retailing

Date	Event
1960s	Wimpy brand established as offshoot of J Lyons
1 970s	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 rebadged 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 3
Estimation of the Determinants of the Hazard of First Entry

Variable	Coeff	t value	mean	effect at mean
Area	-4.295	-6.780	0.5576	
Areasq	0.673	5.130	0.8939	negative
Popn	1.919	4.960	1.0862	
Popsq	-0.147	-3.660	1.9938	positive
Dist	-36.689	-8.000	0.1819	
Distsq	53.298	6.540	0.051	negative
Nbours	-0.156	-1.930	0.7751	
nbours*dist	0.156	2.890	0.8652	
nb dummy	0.639	2.280	0.2709	positive

No. of observations: 6368
Log likelihood –773.41
Dependent variable: Hazard rate of first entry
Method: Non-parametric- no constant, baseline hazard consists of year dummies. PGM hazard model with Gamma distributed unobserved heterogeneity assumed.
Additional variables: 16 year dummies, first 2 year dummies grouped due to no events occurring in the first year.

Table 4
Estimation of the Determinants of the Hazard of Second Entry

Variable	Coeff	t value	mean	effect at mean
Area	-1.210	-1.040	0.2131	
Areasq	0.168	0.280	0.1455	negative
Popn	1.111	4.650	1.5265	
Popsq	-0.432	-1.420	3.0894	positive
Dist	-3.130	-0.63	0.1101	
Distsq	11.010	1.010	0.02	negative
Nbours	0.992	2.510	3.2206	
nbours*dist	-0.440	-1.020	2.9366	
nb dummy	-0.378	-0.090	0.7875	positive

No. of observations: 1274
Log likelihood –238.516
Dependent variable: Hazard rate of second entry
Method: Non-parametric- no constant, baseline hazard consists of year dummies. No unobserved heterogeneity.
Additional variables: 12 year dummies, dummies for years 11 and 12 are grouped together as are those for years 13, 14, 15 and 16. This is due to no events occurring in years 12, 13, 14 and 16.

Figure 1
First-Entry Diffusion

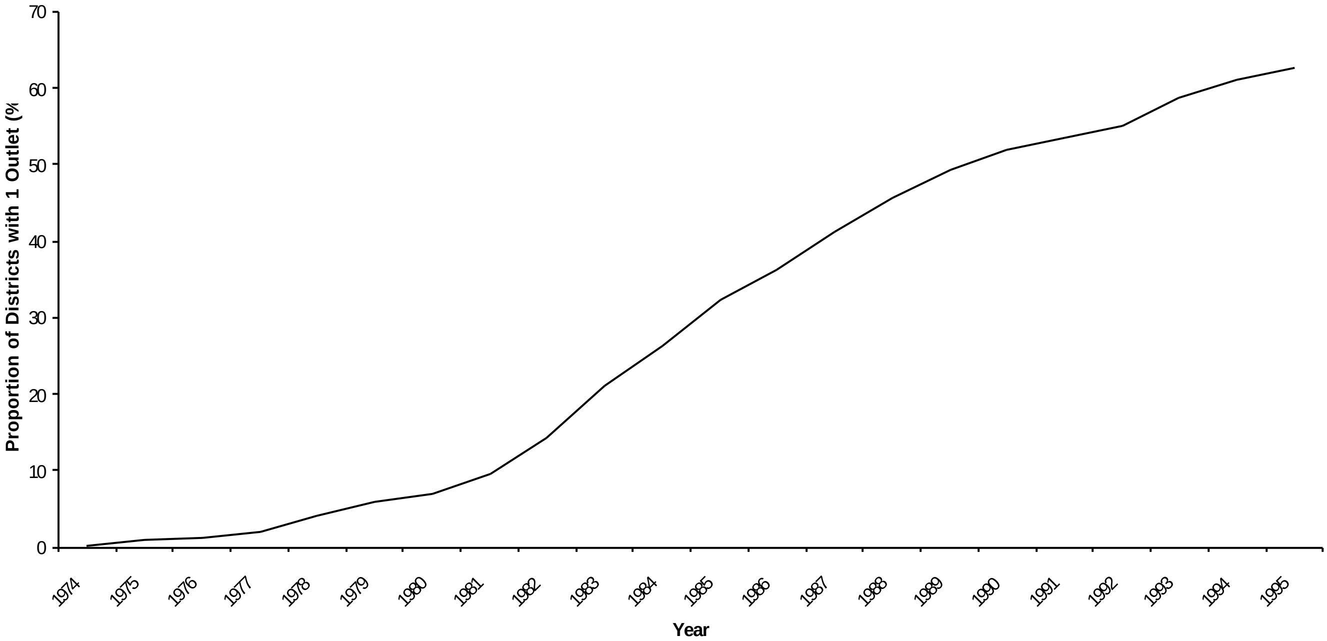
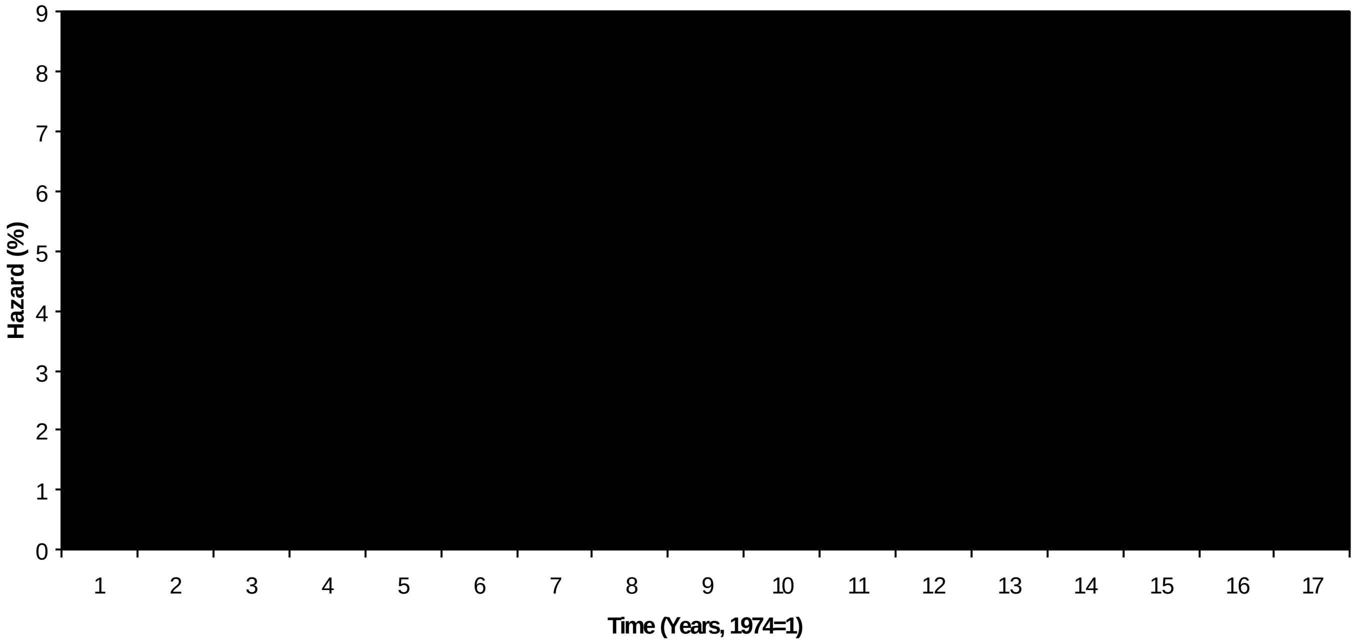


Figure 2
First-Entry Empirical Hazard Rate



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