Discussion Papers on Entrepreneurship, Growth and Public Policy

MAX-PLANCK-GESELLSCHAFT

1205

Market Concentration, Market Dynamism and Business Survival

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Number of Pages: 27

The *Papers on Entrepreneurship, Growth and Public Policy* are edited by the Group Entrepreneurship, Growth and Public Policy, MPI Jena.
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ISSN 1613-8333

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June 2006

Abstract

The paper uses a unique dataset comprising the population of new ventures that enter the UK market in 1998. We argue that we would expect the effect of market concentration on firm survival to be different according to whether an industry is static (low entry and exit) or dynamic. In our empirical analysis we find support for this hypothesis. Industry concentration rates reduce the survival of new plants but only in markets marked by low entry and exit rates. Specifically, a 10 percent increase in the 5-firm concentration ratio or the Herfindahl index in a dynamic market, raises the survival rate of new ventures by approximately 2 percent. Our results suggest greater leniency towards more dominant firms in industries showing buoyant entry and exit rates.

JEL classification: L11, L25, M13 M40

Keywords: new firms, start-ups, survival, dynamism, competition policy, industry concentration

Acknowledgements: Earlier versions of the paper were presented at the EARIE 2005 conference in Porto, a workshop at UCLA in June 2005 and the UK Office for National Statistics (ONS) BDL workshop in 2006. We are grateful to participants for helpful comments. Also we owe thanks to Felix Ritchie and several staff members at the ONS for help with the data. Finally, financial support from Nottingham University through Grant No. NLF A2 RBL6 and from the Leverhulme Trust through Grant No. F114/BF is gratefully acknowledged..

1. Introduction.

One of the main aims of competition policy is the prevention of excessive market power and the abuse thereof.[1] The assumption behind these policies is that high market power, or high rates of concentration, can be detrimental not only to consumer welfare but also to the performance of other rivals in the industry. Related empirical evidence does suggest that high rates of competition and market power are indeed negatively correlated with entry, growth and survival of firms (Caves, 1998). Our paper contributes to this literature by making a simple, yet important point. We argue and provide evidence that the effects of concentration are different for dynamic and static industries. We define markets as dynamic if they are characterised by high rates of entry and exit, otherwise they are considered static.

In order to make this point we focus on one particular aspect of firm performance, namely survival.[2] This is an important topic not only because plant survival shapes the competitive landscape of the economy, but also because the persistence of jobs is linked to the survival of plants. Both of these issues can be expected to impact on welfare in the economy. Specifically, we look at the interactions between industry dynamism (aggregate entry and exit) and measures of industry concentration and find that where dynamism is high (defined as dynamic markets), industry concentration helps new entrants to survive. The distinction between static and dynamic markets largely seeks to distinguish between different dominant forms of competition (see Audretsch et al. 2001), in particular situations where price drives competition (static markets) from those where product and technological innovation play more prominent roles (dynamic markets).

[1] For the European Union, see Articles 81 and 82 of the EC Treaty.
[2] Previous studies on plant or firm survival that considered the importance of concentration include Wagner (1994), Audretsch and Mahmood (1995), Mata et al. (1995) and Görg and Strobl (2003).

We use an exhaustive database of UK VAT registrations from 1997-2002 for our analysis of firm survival. One advantage of our data is that it is essentially a census of all businesses including the smallest of entrants. This is considered extremely important for an accurate description of entry and exit, as these are often small firm phenomena. Secondly, our data is at the plant level which is arguably more appropriate for an analysis of survival since failure of individual plants making up an establishment otherwise goes unrecorded.

The policy implication of our paper is that high levels of concentration and large market shares by incumbents do not necessarily have to be of concern to policy makers as far as the survival of new entrants is concerned. What really matters is what type of market a firm is operating in – whether it is static or dynamic. This is an important finding, as competition policy generally emphasises the possible effects of concentration on static, rather than dynamic markets (Audretsch et al., 2001).

We structure our paper as follows. In the next section we discuss our argument for why concentration and market dynamism matter for survival. Section 3 sets out the empirically model. This is followed in section 4 by a discussion of the data and some summary statistics. The empirical analysis in Section 5 is followed by a summary which concludes the paper.

2. Background to Concentration, Dynamism and Survival

There is little consensus in the literature on whether incumbent firms challenge entrants or not. The conventional view is that industry concentration is associated with incumbent monopoly power and to this end can pose a significant competitive threat for new entrants, i.e., reduce their survival chances. In line with this argument, applying market concentration as a proxy for market power exercised by existing firms, Audretsch et al.

(1991) observe that survival falls with concentration.[3] However, another scenario is possible. Empirical studies indicate that new entrants frequently introduce new innovations to the market and thus pose a threat to incumbents (e.g., Geroski, 1995; Audretsch, 1995a,b). If incumbents are vulnerable to the innovation of new entrants and assuming that some level of monopolistic x-inefficiency has crept into incumbents (Leibenstein, 1966) then high concentration may pose a competitive cushion and permit entrants to successfully contest a market – and increase their chances of survival compared to entrants in other markets. In fact, entry into a less concentrated industry with more efficient incumbents, may pose a much more testing environment for entrants.

Examples of where x-inefficient incumbents unwittingly ceded market share to new entrants abound. The new ventures launched by Richard Branson and his Virgin group of new ventures actually targeted highly concentrated industries where incumbents were not used to competition and were slow to respond (DTI, 1996). Likewise, the new entrants who introduced the 'low cost travel' innovation to the European airline industry benefited from the fact that incumbents were monopolistic x-inefficient firms (such as British Airways and Aer Lingus). The latter had relied on landing slots to block entry and had over time become highly cost inefficient and moreover, were sufficiently inflexible to take a very long time to bring their costs down to competitive levels. This provided crucial breathing space for once small new entrants such as Ryanair and EasyJet to survive (and grow to become large firms). Therefore, either way, market concentration is not necessarily a bad thing for new entrants when competition is innovation-based competition or when x-inefficiencies make incumbents unable to respond to new entry.[4]

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[3] Mata et al. (1995) qualify this finding by observing that very new entrants (those less than 3 years old) affect market share so negligibly that their entry goes unchallenged by incumbents.

[4] We could also look at innovation based competition from the perspective of differentiated products. Consider the price that smart new entrants with differentiated products can charge when they encounter inelastic demand from customers. If the survival of new entrants is enhanced because of the novelty of their product (a genuine innovation), consumer demand is sufficiently inelastic thus allowing new firms a cushion against price cuts

If we accept this argument, then the next question is whether and how the direct effect of competition is moderated by the dynamism of market entry and exit. Since entry and exit rates are highly correlated, we speak of static markets as those where there is little entry and exit. Similarly dynamic markets exhibit high entry and exit rates.[5] We would expect to see different effects of competition on business survival in these two different types of markets.

More specifically, the distinction between static and dynamic markets largely seeks to distinguish between different dominant forms of competition (see Audretsch et al. 2001). In particular, to distinguish situations where price drives competition (static markets) from those where product and technological innovation play more prominent roles (dynamic markets).[6] Thus, in more static environments where new entrants cannot shield themselves from price competition through product and technological innovation (differentiation), the market power of incumbents associated with high industry concentration is likely to pose a major threat to new entrants; implying a negative relationship between concentration and entrants' survival probabilities. By contrast, in more dynamic settings where higher levels of innovation provide a means for entrants to circumvent the competitive advantages of possibly x-inefficient incumbents, high industry concentration may in fact boost the viability of entrants and improve their survival prospects.

To summarise, the potential for market concentration to induce X-inefficiencies implies that it is not always harmful to new venture survival. Moreover, market

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from incumbents. Caves and Pugel (1980) suggest that small firms actively use product innovation as a way of garnering market share in industries with high minimum efficient scale. Product novelty increases the price a new entrant is able to charge its customer base, before customers switch to the next best alternative (incumbent firm's product).

[5] One explanation for this finding that new firms enter despite high industry exit rates (high observed correlation between entry with exit rates) is that any individual firm is unaware of its survival prospects ex ante but becomes aware ex post of its survival chances. This is the conclusion of learning theories in the context of market entry and exit (e.g., Jovanovic, 1982; Pakes and Ericson, 1998).

[6] As Geroski (1995) observes, it is these latter markets which are characterised by high levels of firm entry and exit.

concentration is only expected to confer an advantage to incumbents over new entrants when competition is cost based, i.e., more usually when operating in a static market. If cost based competition is a feature of high concentration levels coupled with low industry dynamism, only under such conditions will market share harm the survival of new ventures. This can be summarised in the following Proposition:

Proposition: The impact of industry concentration on the survival of new entrants is more likely to be negative when markets are static and positive when markets are dynamic.

3. Empirical model

We investigate this issue empirically by modelling a new entrant's hazard of exiting, conditional on a number of covariates. In order to put our study into context, Table 1 summarises some of the stylised facts about business survival and other covariates. There is a consensus that size in general, and attaining minimum efficient scale (MES) specifically, raises a firm's survival prospects.[7] Hopenhayn's (1992) model ties in with the intuition in Gibrat's law that greater size implies a greater capability to capitalise on new opportunities. Analogously, in the 'learning models' first advanced by Jovanovic (1982) and built upon by Pakes and Ericson (1998), hazard rates decline with firm size because larger firms have a higher rational expectation of survival. A significant body of the empirical literature on the survival of new entrants in manufacturing industries has found a positive effect of firms' start-up size on survival.[8]

[7] See Agarwal and Audretsch (2001) for a review of this literature

[8] Evans (1987), Hall (1987) and Audretsch (1991, 1995) have found a positive relationship between survival and firm start-up size for US manufacturing industries. Mata, Portugal and Guimaraes (1995) find similar evidence for Portuguese manufacturing.

Accordingly, we include firm size at start-up in our empirical model. Moreover, industry growth has been found to enhance survival as firms in growing industries may be more likely to avoid competitive pressure from incumbents (e.g., Audretsch, 1991). Hence, we also include this variable in our estimation. Furthermore, Audretsch and Mahmood (1995) argue that survival should be higher in industries that are characterised by high wage rates, as wages may proxy for labour related sunk costs such as training. We also include the median industry wage in our analysis.

In line with much of the literature we use a standard Cox proportional hazard model where we model the probability of firm failure, *f*.[9] As in previous studies, failure is denoted by firms exiting the sample. In other words, firms enter in time *t* and who no longer are VAT registered in time $t+k$ are noted as having failed.[10] The proportional hazard of a firm failing in time *(t)* is formulated as

$$h_f(t) = h(t; x_f) = h_0(t) \exp(X'_f \beta)$$

where *X* comprises a vector of variables impacting on survival based which have been informed by past research (Table 1 and foregoing discussion). These are minimum efficient scale, *MES*, size, *S*, dynamism, *D*, growth, *G* and industry wage, *W*.[11] The term $h_0(t)$ represents the baseline hazard function which describes the probability of death conditional on the firm having survived until time *t* following market entry.

An innovation of our analysis is our focus on the effects of market concentration on survival under different competitive regimes. Accordingly the hazard ratios describing the

[9] See, e.g., Disney et al. (2003), Audretsch and Mahmood (1995), Mata et al. (1995).
[10] We apply a standard convention in survival analyses of this type by classifying exit from the sample as failure. However, exit may be both a temporary as well as a strategic phenomenon (See Fershtman, 1996)
[11] We note that because we examine the survival prospect of cohort, age is invariant over time and is therefore excluded

marginal effect of concentration on failure rates must be allowed to vary according to whether an industry is denoted as dynamic or static. It follows that the validity of any split regression must be evaluated compared to a standard pooled regression by interacting our dynamism dummy against all model covariates and comparing the F test of the standard vis-à-vis the augmented model (the unconstrained model allowing the marginal effects to change under different conditional for market dynamism).

Consistent with standard practice in analyses of this kind, our approach must consider potential for variation in survival rates across different industry sectors. Accordingly, we treat each 2-digit SIC code as a separate stratum and allow the baseline hazard function to vary across these different strata. We should further note that the standard errors estimated in our analyses allow for clustering to occur on an individual firm basis. Accordingly, we use the robust measure of variance in our estimations. In so doing, we recognise that any firm can be expected to behave in a systematic way, and that errors across years therefore, are correlated.

4. Data and Descriptive Statistics

Our data is drawn from the Inter-Departmental Business Register (IDBR) database at the UK Office for National Statistics.[12] This register captures VAT registered businesses and as such comprises about 98 percent of UK business activity.[13] The advantage of using data from the register is twofold. Firstly it is highly representative, given that it covers almost the population of UK firms and does not suffer from biases induced by sampling. This latter point is especially important in duration studies, where over-sampling of large firms in comparison to small firms underestimates the real amount of movement in an economy, since entry and exit is mostly a small firm phenomenon. Secondly, the register

[12] Access to this data is possible under controlled conditions on site at ONS offices.

identifies businesses at the *local unit* level. Barnes and Martin (2002) define this as the "individual site or workplace (factory, shop etc.) at which activity takes place" (p. 37). This is for most cases the level of the plant. Our data is comprised entirely of single plant firms so exit implies firm as well as plant closure.

Higher levels of aggregation (establishment level) used to identify unique firms within the UK Annual Respondents Database (ARD, drawn from mostly larger firms within the IDBR) has up to now made it difficult for researchers to investigate plant exit. An establishment can consist of more than one local unit (plant) and, hence the exit of only one local unit may remain undetected in case the establishment remains alive (albeit with a smaller number of local units).[14] It is also difficult to pinpoint whether the exit of an establishment from the data was caused by the failure of all local units belonging to the enterprise. Alternatively, the exit of an establishment could be induced by the failure of a large and important local unit which in turn caused the whole enterprise to exit from the data. Notwithstanding the exit of the large and important local unit, any sister units could have remained operational if they had been independent entities rather than been part of an enterprise group. To put it simply: an examination of local units is the simplest and arguably most appropriate way to examine entry and exit when we need to directly attribute entry and exit to the unit under examination.

Representativeness and research relevance come at a cost however: While the IDBR contains a reasonably exhaustive listing of all firms from all sectors of the UK economy, knowledge about the features of these firms is limited to sectoral and employment information. To remedy this information shortfall, we import information at a *sectoral* level

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[13] See Barnes and Martin (2002) for an overview of this data.
[14] While the number of local units is in principle observable a reduction in the number may not only be due to exit of local units but could merely be due to an internal reorganisation within an enterprise that may consist of more than one establishments.

on wages and market structure from the ARD data. This lets us describe the composition of the sector in which our firms operate and report, inter alia, industry concentration ratios.

Our data extends for a 6 year period, 1997 to 2002. Focussing on this period is due to one important reason: since 1997, the ARD data cover services as well as manufacturing industries in the UK, while before that year only manufacturing data was available. As an important innovation of our paper is to consider services alongside manufacturing, we analyse data from 1997 onwards.

However, this translates into a relatively short year survival horizon for the cohort of firms who appear in the data for the first time. Data for 1997 is essentially used as a criterion that allows us to identify new entrants (present in 1998 but not in 1997) and data for 2002 allows us to identify real, uncensored exits (present in 2001 but not in 2002). Accordingly, we limit our duration analysis to a 3 year time window when we have accounted for left- and right-hand side censoring and represented failures that arise in 1998 (entry year) as happening at the beginning of the following year.[15]

Fortunately, given the high level of attrition of start-ups in the earliest phases of their operation (almost 50 percent of start-ups exited within these 3 years) even within a relatively short time span we manage to capture a high level of early stage exits. This pattern most likely arises from our ability to include low quality, under-capitalised, start-ups when using the IDBR data. Given the comprehensive nature of the data, we are confident that this data is representative.

Since our analysis focuses on exit from industry sectors, we first report exit levels for the cohort of UK plants entering in 1998, tracking the number of exits from 1998 until 2001.[16] Table 2 presents the development of industry level exit rates, calculated as number of exiting firms in industry *j* relative to the total number of firms in the industry. The

[15] As is customary in survival analyses of this type with 'simultaneous' entry and exit.

average percentage of exits across all firms in the database is about 8 percent per year.[17] This average is slightly higher in manufacturing than in services sector. Overall, this suggests that only a minority of firms across the broad spectrum of UK industry exits in any year. As such, dynamism at a sectoral level appears to happen at the fringes of industry in general, and an examination of all industry exits suggests some inertia.

[Table 2. here]

This inertia seen across UK industry masks the dynamism that arises within cohorts of new ventures, however. Accordingly, we would expect that annual exit rates *within* the grouping of new ventures should be much higher, given the greater financial fragility and unproven track-record of new ventures. **Figure 1** and **Figure 2** trace the hazard rates for our 1998 cohort of UK firms as Kaplan-Meier functions. Attrition is recorded for 3 analysis times and this corresponds to 1999, 2000 and 2001 respectively.[18] We can see from the exit function that almost 25 percent of entrants have died in the year of entry, culminating in a rate of almost 50 percent for the third year of existence, an exit rate in line with others documented for UK manufacturing industries.[19] We moreover split our cohort depending on whether sectoral entry rates at a sectoral level exceed median sectoral entry rates. This allows us to capture possible differences in attrition according as firms enter markets characterised by low and high levels of dynamism respectively.

[16] We cannot calculate the value of exits for 2002 because firm's survival is right censored at this date.
[17] This compares with an average of 6.5% found by Baldwin and Gorecki (1991) for Canadian manufacturing industries. Dunne and Hughes (1994) report an average death rate of 20.5% in their UK data for 1975-85, however, their data comprises only a sample of 2000 quoted and unquoted companies (mainly large) in the UK financial and non-financial companies.
[18] A convention in duration analyses of this type is to treat all failures in the year of entry as having occurred at the beginning of the next year. Accordingly all failure times for entry at time t are treated as failures arising in t+1.

We see from **Figure 1** that firms entering industries with above average entry rates where minimum entry rates are at least 11 percent (‘*high_entry’* = 1) appear *less* likely to survive than their counterparts. This pattern is reflected in the Kaplan-Meier function which formulates entry as a discrete variable.[20] However, we should note that the Kaplan-Meier does not take account of the auxiliary role of other covariates in influencing survival and hence is merely illustrative.

[Figure 1 here]

Figure 2, on the other hand, reports the hazard rates for firms entering industries marked by high dynamism (summation of entry and exit rates), where our dummy variable *‘high_churn’* is set for dynamism rates greater than and equal to the 75th percentile (dynamism ≥ 20%). Here we see that higher hazard rates are registered by firms entering more dynamic industries, a pattern most likely induced by the dominance of industry exit within our measure for industry dynamism. This pattern is also borne out in the positive bivariate correlation coefficient between our dynamism variable *‘churn’* and *‘death’* in **Appendix 1**.

The next step is to analyse whether there is a link between industry dynamism and plant survival taking into account other covariates at the industry and plant level, as discussed in Section 2. **Table 3** shows the breakdown of the covariates used in our analysis. While overall industry sales growth rates in the ARD are shown to be highly volatile across industries and time (as evidenced by the high standard deviation), the variables minimum

[19] Our attrition rate for the 1998 cohort (1st three years), corresponds with other UK exit rates: 42 percent after 2 years cited by Scarpetta (2001) for the early 1990’s and 45 percent in Disney et al., (2003) for the period 1986 to 1991. However, note that these studies only relate to manufacturing industries.
[20] We should note however, the negative correlation coefficient between failure and entry rates (Appendix 1) when firm entry rates are formulated as a continuous variable.

efficient scale, average output of the leading 5 firms in the sector) and median wage rates, show less variation relative to the mean. Our key variable measuring industry dynamism, *'churn'* shows a mean value of 9.8, i.e., the average value for industry dynamism (entry plus exit) is about 10 percent.

Table 4 shows how concentration varies across the industries in our analysis.[21] Concentration records highs in the Tobacco industry and Public Utilities (16 and 40 respectively) and low values are reported for concentration in the Hotel sector and other Services (55 and 93 respectively).

[Table 4 here]

5. Analysis

Our response variable in the model is coded as 1 to signify that the venture has failed. This implies that when interpreting the regression output, hazard ratios of less than 1 mean that the firm's survival chances improve with increases in the exogenous variable. Conversely, hazard ratios greater than 1 show an adverse effect of the covariate on firm survival. We investigate whether proposition 1 holds in our empirical analysis.

Table 5 summarises the results of our Cox duration analysis where the hazard rates of plants in the 1998 cohort are modelled as a function of the industry variables sector, growth, wages, MES and 2 measures of concentration, namely the Hirschman Herfindahl index and the 5 Firm Concentration Ratio.[22] Firm size (number of employees) at the start-up

[21] At the request of the ONS, for industries with fewer than 10 firms, we have not published any information in case individual firms can be identified.

[22] While HHI is arguably the most appropriate measure, an alternative is the five firm concentration ratio (C5) (Sleuwaegen and Dehandschutter, 1986). We also, in alternative regressions, included MES (defined as median size in the industry) in the model, however, the coefficient always turned out statistically insignificant. This may perhaps be due to its correlation with other industry variables. Since inclusion of MES did not change any of the other coefficients of the model we drop MES throughout in order to report the most parsimonious model.

stage is also included as is standard practice in models of firm survival as discussed in Section 2. We first analyse all plants in a pooled framework before going on to explore possible interactions as markets exhibit higher or lower levels of dynamism.

We see from Table 5 that when we use 2 different measures of concentration, the HHI and C5 measure in columns (1) and (2) respectively, that only the latter measure exhibits any statistically significant effect. The market share occupied by the 5 biggest firms is a sufficiently important determinant that a 10 percent increase in the 5-firm concentration ratio decreases the survival rate of new ventures by approximately 8 percent. Another relationship to note is the response of new venture survival to industry growth. Consistent with theories of growth and entry, an increase in industry growth of 10 percent causes survival to rise by approximately 1 percent. This result appears in line with the stylised facts of survival, where growing industries exhibit a higher capacity to absorb new entrants (see Caves, 1998). The high variation in this variable as evidenced by the high standard deviation in Table 3, indicates that even though the coefficient itself is small, industry growth can be of highly important economic significance for plant survival.[23]

In the next step we question the validity of this pooled regression where the competitive regime is taken as a given and no consideration given to industry dynamism. To begin with, we define a dummy variable equal to one if an industry is dynamic. It is defined as such if entry and exit rates combined equal or exceed 20 percent of the stock of firms. This corresponds to the 75th percentile of the distribution of aggregate entry and exit rates. Accordingly we interact all covariates in the model with the industry dynamism dummy and check the Wald for the "augmented" model containing the interaction terms. The explanatory power of this augmented model is better (higher χ^2) than that of its pooled

[23] We also find that firm size has the predicted positive effect on firm survival, although the coefficient is statistically insignificant. This may perhaps be due to the fact that our sample is dominated by services sector

counterpart. Furthermore, the Wald test shows that we can reject the hypothesis that the interaction terms are jointly equal to zero and so we opt on this basis to split our sample along dynamic / static lines.[24]

In Table 6 we report our results for estimating the hazard model on the separate samples of static and dynamic industries respectively. Interestingly, 6,338 firms can be classified using our convention as continuously dynamic for the short period of our study. The majority of firms (98,800) remain classified as static.[25] For those firms entering a static industry, start-up size does not affect survival prospects. Only firms in dynamic industries report start-up size as having adverse consequences for survival. This finding is possibly consistent with a concept of over-investment where cash flow problems can arise. The idea here is based on the common use of staged financing in the face of a limited supply of capital and an uncertain environment with risk milestones. In such circumstances, start-up at smaller size (not drawing down all available finance) allows flexibility in terms of the capability to change/adapt as the venture evolves and market opportunities become more predictable. By contrast scaling up to predicted optimal scale at start-up can limit the available pool of future finance to allow the firm to change strategy should the business develop differently than anticipated. This conclusion follows if industry dynamism is manifested by innovation based competition. According to Agarwal and Audretsch, (2001)

"While the likelihood of survival confronting small entrants is generally less than that confronting their larger counterparts, the relationship does not hold for …… technologically intensive products" [p. 21]

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firms, whereas most of the evidence on the size-survival relationship is based on studies for manufacturing industries.

[24] We do not report these regressions and tests here to save space, but results can be obtained from the authors.

[25] In alternative regressions, dynamism was defined as "dynamism in the year that the new firm enters the industry" giving approx. 30,000 firms for the 1998 cohort. Because an industry's dynamism can evolve (see Geroski, 1995), this implied that some industries move from static to dynamic or vice versa. We revised the definition to mean permanently dynamic or permanently static for our period of study (3 years).

Our key variables of interest are the two concentration measures HHI and C5. Looking at both of these in columns (1) and (2), we find that entrants into static industries encounter significantly lower survival prospects with rising levels of industry concentration. For example, a 10 percent increase in the 5-firm concentration ratio in a static market, reduces the survival rate of new ventures by approximately 20 percent.

We now turn to columns (3) and (4) in order to examine survival in dynamic industries. Here, our concentration measures both improve survival. The point estimate of the hazard ratio suggests that an increase in size of C5 or HHI by 10 percent induces a reduction in the hazard rate of 2 percent (i.e., an increase in the survival rate). This positive relationship between concentration and survival is contrary to what we noted for entry into static industries. It is also consistent with the view that the market share of incumbents can promote survival if it provides a competitive cushion for new entrants.

These results support our key proposition: new entrants into dynamic industries fare better in terms of survival probabilities when industry exhibits higher concentration levels. The reverse appears to hold true for new entrants into static markets.

6. Conclusions

Using a unique dataset of approximately 180,000 UK firms, we track the survival of firms from the 1998 cohort. We model survival using conventional variables used elsewhere in the literature but uniquely, allow for potentially important interactions between industry dynamism (entry and exit) and the effect of market concentration on survival.

Applying two separate concentration measures, we find that concentration actually promotes the survival of new ventures when the industry they enter is classified as dynamic. Specifically, a 10 percent increase in the 5-firm concentration ratio in a dynamic market, raises the survival rate of new ventures by approximately 2 percent. The corollary to the positive effect that we observe of concentration on survival in dynamic industries, is a significant negative effect in static industries. We conclude from this result that only in static industries does concentration harm the survival of new ventures.

Our findings are in line with theories suggesting that x-inefficiencies (symptomatic of high concentration rates) can give rise to a competitive cushion which helps sustain new entrants. Another explanation of our findings is the potentially moderating effect of the technological environment on survival, reported in Agarwal and Audretsch (2001) and Audretsch (1991). Here innovation based competition negates the impact of scale variables such as start-up size and potentially concentration.

From a competition policy perspective, our analysis implies that industry concentration only poses a threat to the viability of new firms in static markets. By contrast, industry concentration actually helps new ventures overcome other impediments to survival such as high risk in dynamic markets. Thus, from an antitrust perspective, the paper provides some key empirical support to the central hypothesis of Audretsch, et al. (2001) who contend that competition policy frequently needs to be different (in its form and conduct) in static and dynamic markets.

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Table 1

Key covariate	Contributer	Prediction / Observation
Size (Size) & MES	Hall (1987) Evans (1987a; 1987b) Dunne et al. (1989) Acs and Audretsch (1990) Scherer (1980) Hopenhayn (1992) Jovanovic (1982) Pakes and Ericson(1998)	$\delta S_i / \delta Size_i > 0$
Growth (G)	Audretsch (1991)	$\delta S_{ik} / \delta G_k > 0$
Industry Wage (W)	Audretsch and Mahmood (1995)	$\delta S_{ik} / \delta W_k > 0$
Dynamism (D)	Geroski (1995)	Dynamism is a feature of the product life cycle and hence every industry at some stage. Industries do not remain dynamic. Dynamism depresses survival rates. $\delta S_i / \delta D_k < 0$ High entry persists until entry pushes the net income of the marginal entrant to Y = 0
Technology (T) and Dynamism	Audretsch, (1995a; 1995b) Mata et al, (1995)	Dynamism (high entry and exit) a feature of industries with high levels of technological change
(1) Concentration (C)	Audretsch et al. (1991) Caves, (1998) Mata et al. (1995)	$\delta S_{ik} / \delta C_k < 0$ $\delta S_{ik} / \delta C_k = 0$ for firms less than 3 years old
(2) Concentration (C)	Weiss, 1976; (1979) Leibenstein, (1966)	$\delta S_{ik} / \delta C_k < 0$ does not hold if P > Production Cost. Instead survival is an increasing function of concentration and market share in the presence of X-inefficiencies i.e. $\delta S_{ik} / \delta C_k > 0$
Concentration (C)and Dynamism (D)	This paper	$\delta S_{ik} / \delta C_k > 0$ with high levels of D $\delta S_{ik} / \delta C_k < 0$ with low levels of D

S denotes firm survival, lowercase i and k denotes firm and industry sector respectively

Table 2: Mean Exit Rates by Year (standard deviation in parentheses)

Year	All sectors	Manufacturing	Services
1998	0.078 (0.052)	0.086 (0.057)	0.078 (0.053)
1999	0.088 (0.060)	0.094 (0.057)	0.088 (0.060)
2000	0.088 (0.059)	0.092 (0.059)	0.087 (0.060)
2001	0.081 (0.059)	0.083 (0.052)	0.081 (0.059)

Source: own calculations based on ONS data

Table 3: Descriptive Statistics

	Mean	Std. deviation
Herfindahl index	0.0031	0.0334
C5	0.039	0.063
Churn	9.831	14.279
Industry growth	16.348	114.025
MES	9,361	14,832
Median industry wage	200.906	586.114
Start up size	5.17	40.03

Source: own calculations based on ONS data

Table 4: Industry Concentration and Dynamism

Sector	hirschman (m_hirsh)			5-firm conc. (c5)			dynamism (churn)		
	No.	mean	std. dev.	No.	mean	std. dev.	No.	mean	std. dev.
Manufacture of Food (15)	6,556	1.94	2.0	6,556	20.2	11.1	6,556	26.4	7.7
Tobacco (16)	101	63.2	26.2	101	95.5	3.5	101	50.4	6.9
Textiles (17)	3,849	1.18	0.7	3,849	15.5	6.0	3,849	23.5	5.5
Clothing (18)	3,660	0.56	2.5	3,660	5.7	10.5	3,660	32.9	7.8
Footwear (19)	455	2.18	1.8	455	22.9	12.1	455	21.5	7.7
Timber products (20)	3,078	0.36	0.8	3,078	6.5	6.3	3,078	17.4	4.5
Paper products (21)	1,233	0.68	0.7	1,233	9.0	6.7	1,233	19.1	4.1
Publishing (22)	13,861	0.355	0.7	13,861	6.8	7.6	13,861	24.0	7.7
Oil and refining (23)	392	12.7	9.0	392	61.4	11.3	392	27.3	8.7
Chemicals (24)	3,262	2.25	2.5	3,262	22.3	11.5	3,262	24.6	4.9
Rubbers and plastics (25)	2,570	0.57	1.1	2,570	6.6	9.0	2,570	16.5	4.5
Glass and ceramics (26)	3,851	2.65	4.0	3,851	23.6	16.4	3,851	24.1	6.3
Iron and steel (27)	2,213	2.32	3.9	2,213	21.1	9.8	2,213	22.4	6.7
Metal products (28)	10,368	0.23	0.6	10,368	4.1	6.1	10,368	17.5	8.9
Machinery (29)	4,706	0.91	1.7	4,706	11.1	11.3	4,706	16.7	5.2
Computers and office machinery (30)	877	3.33	0.3	877	32.8	2.5	877	37.2	10.1
Electrical equip. (31)	2,011	1.62	1.9	2,011	19.8	10.7	2,011	19.9	8.9
Radio and TV equip. (32)	1,143	3	1.2	1,143	29.9	6.8	1,143	22.2	6.6
Electronic and optical devices (33)	2,104	1.41	1.3	2,104	17.3	9.5	2,104	20.4	8.4
Motor vehicles (34)	1,235	2.61	3.2	1,235	23.5	18.3	1,235	20.9	5.9
Other transport equip. (35)	1,484	6.45	2.5	1,484	44.5	9.7	1,484	30.8	9.9
Furniture (36)	9,729	0.32	0.6	9,729	7.1	5.5	9,729	25.0	7.7
Recycling (37)	625	0.94	0.5	625	12.7	4.2	625	32.8	7.6
Electricity (40)	415	16.6	9.6	415	68.1	12.0	415	58.6	12.4
Water (41)	100	17	6.2	100	78.6	11.9	100	60.0	5.1
Construction (45)	71,233	0.03	0.1	71,233	2.2	1.6	71,233	0.7	5.2
Vehicle retail (50)	25,836	0.06	0.1	25,836	2.1	2.5	25,836	20.0	5.5

Table 4 (Ctd.): Industry Concentration and Dynamism

sector	hirschman (m_hirsh)			5-firm conc. (c5)			dynamism (churn)		
	No.	mean	std. dev.	No.	mean	std. dev.	No.	mean	std. dev.
Other wholesale (51)	48,991	0.06	0.0	48,991	3.2	1.2	48,991	23.7	6.7
Retail (52)	161,901	0.15	0.3	161,901	3.2	3.3	161,901	3.4	10.5
Hotels and restaurants (55)	51,012	0.04	0.4	51,012	1.4	2.9	51,012	2.8	8.6
Transport (60)	18,075	0.38	3.4	18,075	3.2	9.0	18,075	0.6	4.5
Other transport (61)	828	2.4	1.3	828	26.1	27.3	828	27.3	5.6
Air transport (62)	737	5.45	2.6	737	42.8	42.8	737	29.1	8.3
Travel agents (63)	6,642	1.24	1.5	6,642	15.6	15.6	6,642	25.4	6.4
Post (64)	11,345	11.48	27.8	11,345	22.1	22.1	11,345	46.7	8.7
Banking (65)	701	71.38	28.6	701	91.4	91.4	701	100.0	0.3
Insurance (66)	103	6.76	0.3	103	46.1	46.1	103	53.0	0.0
Other finance (67)	181	6.76	1.6	181	39.1	39.1	181	75.0	2.4
Real estate (70)	30,575	0.05	0.0	30,575	2.8	1.0	30,575	24.8	5.5
Rental (71)	8,668	0.37	0.8	8,668	6.8	5.2	8,668	28.8	8.1
Consultancy (72)	110,641	0.07	0.2	110,641	2.6	3.0	110,641	4.7	14.2
R&D (73)	1,066	2.8	2.1	1,066	22.5	9.1	1,066	20.7	5.4
Professional (74)	144,351	0.1	0.2	144,351	3.6	3.1	144,351	5.9	14.2
Education (80)	19,270	0.38	0.4	19,270	7.0	4.6	19,270	31.6	12.9
Nursing (85)	28,095	0.05	0.0	28,095	2.7	1.6	28,095	22.7	12.1
Refuse (90)	798	2.44	2.1	798	24.3	14.5	798	31.6	7.4
Organisations (91)	86,022	0.09	0.2	86,022	3.2	2.5	86,022	7.9	3.8
Cinemas (92)	31,944	0.45	1.1	31,944	6.6	6.8	31,944	14.7	14.2
Other services (93)	43,089	0.01	0.0	43,089	0.9	0.1	43,089	**0.0**	0.0

Table 5: Hazard functions for Dynamic and Stable Markets

Stratified Cox: failure = 1	(1) Pooled Regression	(2) Pooled Regression
startup size	0.9997 (0.0002)	0.9997 (0.0002)
HHI	0.9997 (0.0002)	
C5		1.008 (0.0019)***
industry growth	0.9994 (0.0002)***	0.9996 (0.0002)**
median wage	1.000 (0.0000)	0.9999 (0.0000)
sector dummies	yes	yes
Obs	554,738	554,890
Firms	179,143	179,144
Wald ratio		
Wald (p-value)	(0.0000)	(0.0000)

Source: Observations calculated from Inter-Department Business Register (IDBR) data at Office for National Statistics. Industry level data calculated from Annual Respondents' Database (ARD) at same source

Notes: Stratified by industry sector (SIC92 2-digit). Coefficients are hazard ratios. Also report Robust standard errors: errors clustered within plants across time. *, **, *** denotes statistical significance at 10, 5 and 1 % level respectively.

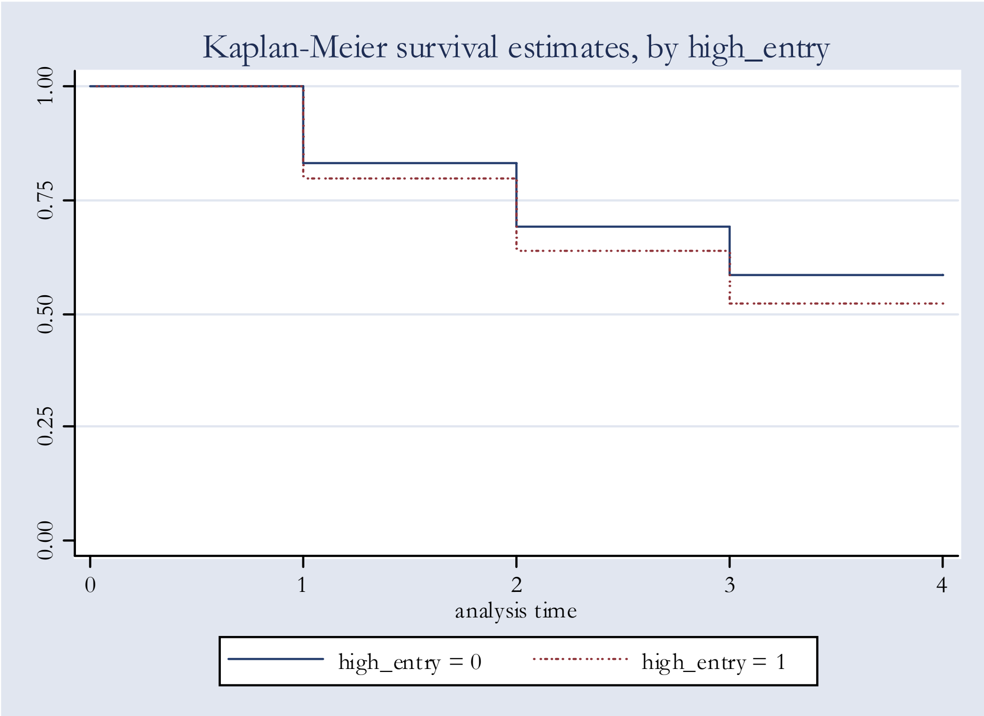
Table 6: Survival and continual market dynamism

Stratified Cox: failure = 1	always static		always dynamic	
	(1)	(2)	(3)	(4)
HHI	1.145			
	(0.029)**		0.998	
			(0.001)**	
C5		1.022		0.998
		(0.007)***		(0.001)*
startup size	0.999	0.999	1.002	1.002
	(0.001)	(0.001)	(0.001)***	(0.001)***
industry growth	0.999	1.000	0.999	0.999
	(0.001)	(0.001)	(0.001)	(0.001)
median wage	0.999	0.999	0.999	0.999
	(0.000)	(0.001)	(0.001)	(0.001)
sector dummies	yes	yes	yes	yes
obs	286386	286386	17736	17736
firms	98800	98800	6338	6338
Wald (p-value)	30.38	35.41	48.11	44.94

Source: Observations calculated from Inter-Department Business Register (IDBR) data at Office for National Statistics. Industry level data calculated from Annual Respondents' Database (ARD) at same source

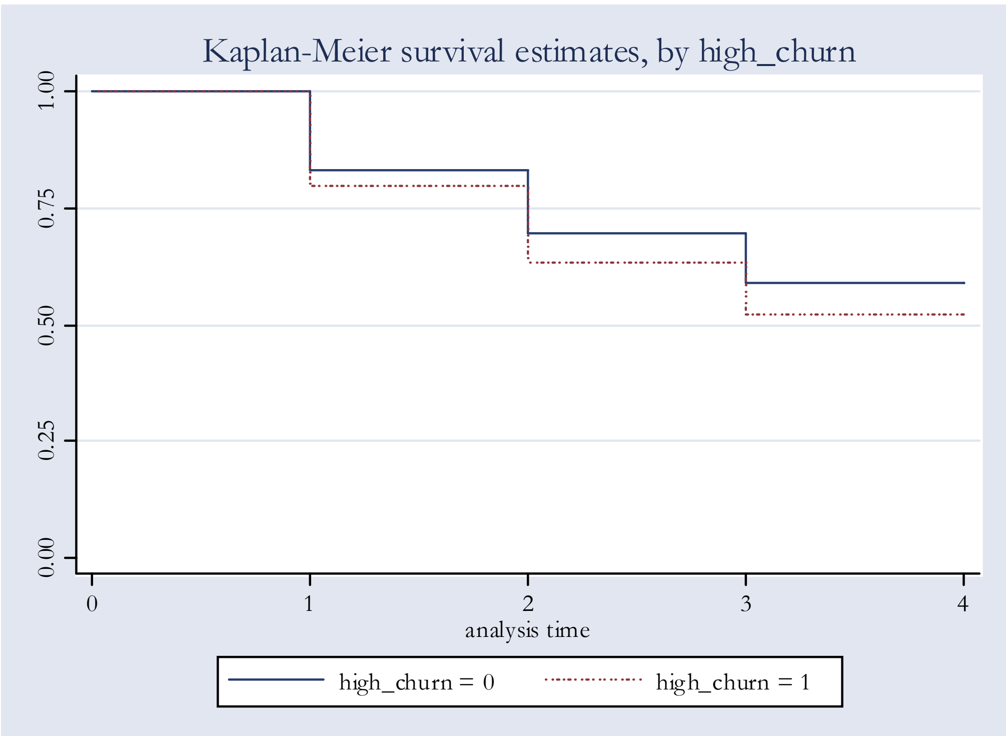
Notes: Stratified by industry sector (SIC92 2-digit). Coefficients are hazard ratios. Also report Robust standard errors: errors clustered within plants across time. *, **, *** denotes statistical significance at 10, 5 and 1 % level respectively.

Figure 1



Estimated using data from ONS, UK

Figure 2



Estimated using data from ONS, UK

Appendices

Appendix 1 Correlation matrix

	death	start_~e	m_hirsh	ind_gr~h	mes	wage_med	sales_~d
death	1						
start_size	0.0066*	1					
m_hirsh	0.0105*	0.0124*	1				
ind_growth	0.0066*	-0.0054*	-0.0023	1			
mes	-0.0030*	-0.0059*	0.1048*	-0.0053*	1		
wage_med	0.0098*	0.1107*	0.0681*	-0.0260*	-0.0755*	1	
sales_med	0.0246*	0.1221*	0.1014*	-0.0272*	0.0153*	0.5912*	1
entry_r	-0.0135*	0.0228*	0.0889*	-0.0079*	-0.1486*	0.1573*	0.0965*
churn	0.0503*	0.0388*	0.1706*	-0.0099*	-0.1937*	0.3295*	0.2822*

Estimated using data from ONS, UK

Appendix 2 List of Variables

death = 1	Enterprise has exited
start_size	Employment size at time of start-up
m_hirsh	Sum of squared employment shares from ARD within 3-digit sector
ind_growth	Annual growth from ARD of 3-digit sector
mes	Average turnover from ARD of 5 largest firms in 3-digit sector
wage_med	Median wage from ARD in 3-digit sector
entry_r	Entry rate from IDBR in 3-digit sector
churn	Entry and exit rates from IDBR in 3-digit sector
high_churn =1	Dynamism greater than 20 percent
high_entry =1	Entry rate greater than 11 percent
id	Local unit identifier (single-plant)

Source: Estimated using data from ONS, UK

Notes:

ARD denotes that the variable (an aggregate variable matched on sector) was calculated from selected firms within the data captured from the annual survey of respondents (selected sample). IDBR denotes the wider frame of data comprising firms from within the selected as well as non-selected database.