DEPARTMENT OF MANAGEMENT

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AN ECOLOGICAL THEORY OF POPULATION-LEVEL ORGANIZATIONAL DIVERSITY*

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ABSTRACT

The question as to the evolution of population-level organizational diversity is at the heart of macro-level organizational sociology. However, the number of studies that direct this question explicitly is very limited, particularly in the empirical arena. We suggest a diversity-dependence theory that maps the macro-level evolution of organizational diversity with the micro-level events of entry and exit. We develop hypotheses as to the decision where to locate in product space by new entrants, as well as the likelihood of exit by incumbent firms given their location in product space. The key argument is that the micro-level entrants' location decision and incumbents' exit likelihood are both conditional upon macro-level organizational diversity, and that these events affect the evolution of population-level organizational diversity. Our hypotheses are tested in the British motorcycle industry in the 1895-1993 period, where we find support for our theory.

INTRODUCTION

How does organizational diversity evolve? Which are the forces behind its increase or decrease? What are its implications for how organizations behave? Since the early work of sociologists like Durkheim (1893), these questions have attracted the attention of a wide array of scholars in fields as diverse as strategic management (Caves and Porter, 1977), institutional theory (DiMaggio and Powell, 1983), and organizational ecology (Hannan and Freeman, 1977). Such questions are important because organizational diversity represents the dynamo of evolutionary change upon which selection operates (Astley, 1985). Organizational diversity has important implications at different levels of analysis. Diversity impinges on career opportunities (Hannan, 1988), affects innovation potential (Grabher and Stark, 1997), stimulates learning at the population level (Jacobs, 1969; see also Ingram, 2002), and determines the adaptive capacity of industries and communities by setting the limit to the available alternatives (Romanelli, 1991; Carroll and Hannan, 2000; Acs and Armington, 2004). Notwithstanding its major theoretical and empirical importance, the number of studies that explicitly focus on diversity as the major variable of interest is limited (Ruef, 2000; McKendrik, Jaffee, Carroll, and Khessina, 2003). In this paper, we focus on developing a theory of the dynamics of population-level organizational diversity, testing our hypotheses in the British motorcycle industry in the 1895-1993 period.

It should be recognized beforehand that organizational diversity can be mapped with respect to several organizational properties including goals, systems of authority, technologies and marketing strategies (Romanelli, 1991; Rao, Morrill, and Zald, 2000; Pólos, Hannan, and Carroll, 2002). Two distinct approaches to define organizational diversity emerge from prior work. Some scholars have stressed the core features that discriminate the way in which organizations transform inputs into outputs – i.e., the organizational blueprints (Hannan and Freeman, 1977). Several others have focused on differences in products or services offered (i.e., outputs) to infer organizational diversity (see Romanelli, 1991). In the present study, we use the positions of motorcycle producers in product space (based on the engine capacity of output) to map organizational diversity. We opted for this approach for two reasons. First, empirical research shows that the fate of organizations is inextricably linked to the positions they occupy in product space (e.g., Baum and Singh, 1994a, 1994b). These positions define the niches in which social action (collective and individual) unfolds (Dobrev, Kim, and Hannan, 2001), which also allows one to model the relational nature of symbiotic and competitive interactions between firms in different market segments (Baum and Haveman, 1997; Dobrev et al., 2001; Dobrev, Kim, and Carroll, 2002). Second, we build on a long-standing ecological tradition treating organizational blueprints and niches as closely related (e.g., McPherson, 1983). Therefore, we assume that repositioning is associated with significant process losses (Hannan and Freeman, 1984; Dobrev et al., 2001). Given this link between product positions and organizational blueprints, we argue that the distribution of organizations in product space firmly reflects the diversity of organizations within a population. More precisely, we define population-level diversity as the aggregate variety and abundance of positions in resource space.[1]

The present paper is especially concerned with the evolution of population-level diversity. Prior work on the dynamics of diversity can be divided into two strands (Fombrun, 1988). The first strand explores the processes leading to organizational convergence. According to institutional theory, organizations become homogeneous because similarity provides them with the legitimation necessary to survive. As DiMaggio and Powell (1983: 149) put it, isomorphism “forces one unit in a population to resemble other units that face the same set of environmental conditions.” Homogeneous resource environments winnow macro-organizational diversity also via competitive exclusion (Hannan and Freeman, 1977; Astley, 1985). The second strand of research focuses on the processes leading to organizational divergence. The so-called ecological models of localized competition claim that crowding leads to differentiation of organizational domains (Hawley, 1950; Baum and Haveman, 1997). Empirical research on niche overlap (McPherson, 1983; Baum and Singh, 1994a, 1994b) belongs to this tradition.

Each of these two perspectives provides interesting but partial insights on the dynamics of organizational diversity, either stressing the forces leading to convergence or those leading to divergence. The present work expands this argument by developing a more comprehensive, multi-level, non-recursive theory of industry evolution in which the interplay between industry structure (i.e., population-level diversity) and firms’ outcomes (i.e., firm entry and exit) is modeled as dynamic and iterative (cf. Carroll and Hannan, 2000: Figure 2.6 on page 31). More specifically, building on Hawley (1950), we envision populations as communities of organizations characterized by the co-existence of blending (mutualism) and segregation (competition) processes. Organizations are drawn to similar positions in resource space because of the positive spillovers that result from externalities, while similarity in positions at the same time increases crowding and competition, which push organizations in the direction of relatively empty niches. As a result of these counteracting forces, organizations face a trade-off between similarity and differentiation vis-á-vis competitors. We believe that the outcome of this trade-off depends on the aggregate distribution of firms in the resource space (i.e., population-level diversity). Specifically, we claim that aggregate diversity drives entrepreneurial entry location in product space, and serves as a map for positional change and performance of incumbent organizations. Together, these firm-level actions feed back into aggregate diversity, renewing the map for future organizational decisions. The end result is a diversity-dependence theory linking the dynamics of aggregate diversity to entries and exits.

Clearly, we build on niche overlap and resource partitioning theories, whose roots go back to Hawley's (1950) seminal work. We, however, extend niche overlap research in two ways. First, while niche overlap theory has primarily focused on the processes of differentiation resulting from crowding, we also theorize on the antecedents of crowding and on the origins of competitive overlap. By doing so, we integrate the forces of divergence and convergence into a unified framework. Second, we move beyond studying the consequences of relative firm-level positioning by modeling the dynamic interplay between firm-level overlap and population-level positional diversity. So, our approach spans multiple levels of analysis, linking firm-level niche positioning with industry-level outcomes and vice versa (for a similar logic, see also Dobrev et al., 2002).

The most comprehensive theory to date on the dynamics of organizational diversity is probably resource partitioning (Carroll, 1985). It is comprehensive as it represents an attempt at developing an evolutionary theory of industry structure in which forces of population-level concentration (convergence among generalists) go hand in hand with specialist proliferation (divergence). The theory explains how market concentration leads to the proliferation of specialist organizations, and hence to bifurcated populations. Although largely inspired by resource partitioning, we aim at describing a different process of niche partitioning. Two theoretical differences do exist between Carroll's (1985) model and ours. First, in resource partitioning organizational convergence stems from scale economies that pull competitors toward the market center (see, e.g., Freeman and Audia, 2006). We claim that convergence may also emerge <u>independently</u> from scale economies, resulting from mutualism driven by positive externalities. Second, resource partitioning describes the <u>sequential</u> development of <u>sustainable</u> bifurcation (i.e., differentiation which is hard to reverse) between generalist and specialists due to scale-based competition among generalists. Our non-recursive, multi-level theory stresses the emergence of a more complex division of labor where periods of convergence alternate with periods of divergence, and vice versa.

By structuring our reasoning on the forces of mutualism and competition, the present theory may also be considered complementary to density dependence logic (Hannan, 1986). Whereas density dependence focuses on the evolution of the number of firms within a population, our theory points to the positional dynamics of a given number of organizations in resource space. Therefore, the two theories study complementary features of organizational populations – i.e., the <u>number</u> of firms and their <u>distribution</u> in resource space. We believe that by using the logic of this well-established ecological theory to study a set of complementary outcomes, cumulative knowledge on population-level dynamics can be considerably extended.

Below, starting from Hawley's insights, we will first introduce resource partitioning as a major evolutionary theory of population-level structure. Next, we stress the dialectical tension between convergence and divergence that guides organizational location in resource space. We contribute to this debate by showing how the <u>firm-level</u> trade-off between similarity and dissimilarity depends on the overall degree of <u>population-level</u> diversity. We formulate hypotheses with respect to the interplay between population-level diversity and the positional similarity vis-à-vis competitors of (i) disbanding incumbents and (ii) new entrants. We test these hypotheses in the British motorcycle industry during the 1895-1993 period. In carrying out our empirical study, we will be careful to rule out several alternative explanations related to density-dependence, resource partitioning and industry-aging arguments. Moreover, we will run robustness analyses to investigate the importance of positional change by incumbents vis-à-vis entries and exits.

HAWLEY AND RESOURCE PARTITIONING

The work of Hawley (1950, 1986) has drawn attention to how collective life revolves around interdependencies that can either be mutualistic[2] (when units increase each other's viability) or competitive (when they decrease it). The dominant type of interdependence varies in time and space, with obvious implications for the evolution of population-level organizational diversity. Specifically, his theory of competitive social processes (Hawley, 1950: 202-203) advances a four-stage model according to which the structure of communities evolves from competitive to mutualistic interdependencies. The first stage begins when the number of units with similar demands exceeds the supply of resources, engendering competition. Second, faced with same environmental conditions, uniform responses intensify competition. As a result, the weakest competitors are eliminated during the third stage. Finally, competition resolves itself as less fit competitors differentiate away via territorial or functional transformation. Thus, "the final outcome of competition is a more complex division of labor characterized by primarily symbiotic relations between social units" (Carroll, 1985: 1278).

Several theory fragments within organization ecology draw from Hawley (1950). Two of the most prominent examples are niche overlap (McPherson, 1983;

Baum and Singh, 1994a, 1994b) and resource partitioning (Carroll, 1985; Carroll and Swaminathan, 2000). Niche overlap theory (McPherson, 1983) has primarily contributed to clarifying the mechanisms of competitive differentiation. Baum and Singh (1994a) and Baum and Oliver (1996) find evidence that high niche overlap decreases entry in the focal niche. Similarly, Baum and Singh (1994b) reveal that niche overlap density is positively associated with mortality rates. Baum and Singh (1996) report also that differentiation – i.e., moving to less competitive niches – increases day care centers' survival chances.

Although niche overlap is informative on the relationship between crowding and differentiation at the firm level, the theory does not explicitly deal with the dynamics of aggregate diversity. By contrast, resource partitioning elaborates on the interaction between micro-level niche processes and the evolution of population structure – i.e., concentration and density. Carroll (1985) elaborates upon his theory starting from two ideal-types of organizational strategy profiles: generalists and specialists. A generalist organization aims its products at a broad range of consumer tastes in the market; it does so by making products or services with a broad appeal. A specialist organization, by contrast, shoots for a small range of very specific customer tastes (Hannan and Freeman, 1977). Accordingly, a generalist's target range or niche is a broad region in the market, whilst a specialist occupies a small spot in the resource space's periphery (Carroll, 1985; Péli and Nooteboom, 1999). The theory contains two sequential parts: one dealing with generalists' behavior and the other with the viability of specialists.

Under the specific condition of scale economies, generalists maximize their appeal by focusing on the densest, central, region of the resource space. This ignites an intense scale-based competition among generalists for the market center. As a result, only the largest generalists squarely positioned in the market center will survive. This is the theory's first part. The second part of the theory predicts that the dominance of large-scale generalists in the center (and thus increasing generalist concentration) creates opportunities for specialists to supply those segments of the market that generalists, by strategic necessity, cannot serve. Consequently, generalist concentration increases the viability of specialist organizations in the periphery (i.e., by increasing their founding rates and reducing their mortality). Evidence indeed abounds that generalist concentration increases the viability of differentiators (for an overview, see Carroll, Dobrev, and Swaminathan, 2002).

Obviously, the logic of resource partitioning is similar to Hawley's sequential stage model. Scale economies trigger uniform responses and pull firms to similar positions (i.e., stimulating convergence). Eventually, only large generalists can survive, opening up opportunities for specialist organizations. The end result of this process is a bifurcated market where concentration among generalists (reducing organizational diversity) is accompanied by the proliferation of specialist firms (increasing organizational diversity). So, "both Hawley's model and the resource partitioning model generate the same differentiated social system in equilibrium … and predict a shift from competitive to symbiotic relations between organizational forms" (Carroll, 1985: 1278).[3] The interdependence between generalists and specialists is symbiotic as they develop into units of different form. Carroll and Swaminathan's (2000) clearly illustrate this point in the US brewing industry, where brewpub and microbrewery's identities sharply differ from those of mass brewers. Similarly, Boone, Carroll, and van Witteloostuijn (2002, 2004) demonstrate that only specialists whose niches do not overlap with the generalists benefit from concentration in the market center. Segregation is not only sustained by cultural processes of identity formation, but also because concentration creates entry barriers in the market center.

A NON-RECURSIVE THEORY OF POPULATION-LEVEL DIVERSITY

Our theory aims at describing partitioning processes of a different kind that rely on positive externalities (i.e., commensalism) as a major force of convergence instead of scale economies, and that allow for population-level outcomes other than bifurcation or segregation between forms (cf. Dobrev and Kim, 2006). We start our reasoning from Hawley (1950: 40), too, who suggest that "the significance of competition is often emphasized to the exclusion of the mutual support like organisms render one another… an aggregate acting in concert can accomplish what a lone individual cannot." Population-level similarity with respect to resources not only increases competition, but also simultaneously enhances commensalism via positive externalities. Several sources of externalities associated with positional similarity have been identified in the literature. Similarity facilitates the sharing of infrastructures and the creation of economies of standardization (Wade, 1995; Baum and Haveman, 1997). It also enhances the development and accumulation of common knowledge that spills over from one firm to the other proportionally to their overlap in resource space (for a review in the R&D literature, see Kaiser, 2000), and facilitates vicarious learning (Delacroix and Rao, 1994). Finally, crowding breeds legitimation. Evidence for this has been presented in the literature on the emergence of new forms (e.g., Ruef, 2000; McKendrick et al., 2003), showing that legitimation is more likely to spill over from an incumbent to a new entrant when the latter is similar to the former.

As mutualism and competition co-exist, both interdependencies should not necessarily be seen as states alternating in time, as in Hawley' stage model or in

Carroll's resource partitioning theory. Instead, they can also be envisioned as counteracting forces that are at work simultaneously (see also Dobrev and Kim, 2006). As will be explained below, because the potential for mutualism is likely to persist over the entire evolution of populations, our theory allows for population-level dynamics in which periods of convergence (decreasing population-level diversity) alternate with periods of divergence (increasing population-level diversity), and vice versa.

Population-level diversity dependence

The continuous co-existence of mutualistic and competitive interdependencies creates a conundrum for organizations (either incumbents or newcomers): should they be similar with respect to their position vis-à-vis competitors or should they be different (Baum and Haveman, 1997)? On the one hand, similarity provides potential benefits of mutualism due to positive externalities, but also increases competition for scarce resources. On the other hand, differentiation provides competitive relieve, but, at the same time, erodes the spillover of positive externalities. Because organizations in a population share a common fate, forces of convergence and divergence push them towards similarity (i.e., decreasing population-level homogeneity) and simultaneously towards differentiation (i.e., increasing population-level diversity).[4]

It should be clear that the outcome of the firm-level trade-off between similarity and differentiation depends on the actions of competitors. Those that choose to imitate enjoy the benefits of positive externalities and mutualism. However, if every organization decides to be similar to the others, the downsides of competition may outweigh the benefits of clustering together. In other words, imitation by individual organizations then increases similarity to the extent that a compensatory increase in the degree of rivalry exhibited by the population is created (Fombrun, 1988). Under these conditions, dissimilar organizations enjoy relative advantages vis-à-vis competitors.

Hence, a dialectical tension between convergence and divergence ensues: the trade-off between similarity and differentiation is dynamic and depends on the sum of the imitative behavior of other organizations – i.e., on the aggregate degree of population-level diversity. Figure 1 shows a representation of this multi-level phenomenon in system dynamics terms, where a convergence (positive) and a divergence (negative) feedback loop are at work simultaneously.

INSERT FIGURE 1 ABOUT HERE

Population-level organizational homogeneity (or, conversely, population-level diversity) is the central concept of Figure 1.[5] On the one hand, homogeneity enhances the creation of 'common assets' and the spillover of macro-level externalities between organizations. In this scenario, firms have incentives to be similar, and micro-level imitation is observed. At the aggregate level, imitation carried out by entrepreneurs entering the population or by incumbent organizations changing their position augments population-level homogeneity, further increasing the potential for externalities – hence the positive feedback loop. On the other hand, when organizations are too similar, high aggregate homogeneity triggers competition, which spurs differentiation by incumbents or newcomers. Differentiation reduces population-level homogeneity and thus competition – hence the negative feedback loop.

Two general principles follow from the dynamic system presented above. First, at the macro level, given (constant) population-level carrying capacity, there exists some kind of 'optimal' distribution of organizations in product space – i.e., an equilibrium level at which the forces of convergence and divergence are balanced (see also Wezel and van Witteloostuijn, 2006). A similar general principle has been raised by Hawley (1986) in the context of human ecology. Specifically, "in any given state of local transportation technology, there tends to be an optimum density of concentration, a density that is most conducive to the efficient functioning of the system. Too low a density makes for relatively high costs of conducting exchanges of all kinds and allows destabilizing influences to enter the system. Conversely, too great a density raises costs through time lost in congestion and related frictions, introducing different destabilizing forces." This argument relates to the distribution of organizations (or human beings) in geographical space. Lomi and Larsen (1996) built on this insight in their simulation study, revealing that when too few firms occupy a focal firm's neighboring niches, this firm dies of solitude, whilst too high neighboring density generates competition and hence "suffocation". We start from a similar argument that too high a concentration of organizations in resource space – i.e., population-level homogeneity – destabilizes the system by increasing competition. Too low such homogeneity, however, destroys the benefits of collective action and mutualism, increasing the need for similarity.

Second, at the firm level, the extent to which similarity or differentiation will provide survival advantages depends on the distribution of organizations in resource space. To make precise predictions, however, we have to introduce minimal assumptions with respect to the shape of the relationship between population-level homogeneity, on the one hand, and macro-level competition and externalities, on the other hand. Here we follow standard organizational ecology reasoning. First, given a fixed resource base or carrying capacity, competition increases more rapidly the more organizations produce similar products. That is, the principle of competitive exclusion implies that competition increases with industry homogeneity at an increasing rate.

Second, it is reasonable to assume that the marginal impact of ‘adding’ a similar organization to a pool of organizations on the creation of ‘common assets’ decreases with the number of similar organizations in the pool. Given a fixed carrying capacity, population-level homogeneity then breeds externalities at a decreasing rate.

The result is that, at high population-level diversity, aggregate niche overlap and thus competitive pressures are relatively low so that the benefits of similarity will dominate (i.e., the positive feedback loop). Then entrepreneurs will enter with products similar to the incumbents’, incumbents will imitate each other’s niche position, and incumbents isolated in product space will fail. The re-iteration of these micro behaviors and events reinforces population-level homogeneity, increasing aggregate competitive pressures at an increasing rate. Therefore, at high population-level homogeneity, centrifugal forces (i.e., the negative feedback loop) will dominate, and differentiation will improve survival. Newcomers will locate in less populated niches, incumbents will differentiate away from crowded segments, and isolated incumbents will prosper, renewing organizational diversity. The result is an endogenous ecological theory of population-level diversity dependence.

Note that firm-level differentiation does not only follow from crowding, but can also be induced by exogenous shocks, such as technological change and other discontinuities (Tushman and Anderson, 1986). In addition, differentiation might reset the feedback loop of imitation if entrant entrepreneurs or incumbent organizations spot the successful variations. In such cases, a new cycle of homogenization might be set in motion around a new target of attraction. This direct link between firm-level differentiation and imitation is important as it impinges on the trajectory of population-level homogeneity (or diversity) over time. It is clear that the combined positive and negative feedback loops without such direct link produce an S-shaped trajectory of homogeneity towards a system-level equilibrium of homogeneity, possibly with oscillations around this level (e.g., when some effects only materialize after a delay: cf. Sterman, 2000). The direct link, however, would imply the occurrence of oscillations over time around shifting targets of attraction. Periods of convergence would be followed by periods of divergence, and vice versa. We further discuss this issue in the appraisal.

DIVERSITY-DEPENDENT HYPOTHESES

The purpose of the remainder of the paper is <u>not</u> to develop a full-blown empirical test of the theory presented in Figure 1. This would require building complex systems of simultaneous equations at different levels of analysis, namely the firm and the population. To the best of our knowledge, given the current state of the art in econometrics, this would be unfeasible. Instead, our theory allows us to develop precise predictions with respect to the impact of population-level homogeneity on firm-level entry and exit behavior. Specifically, we test three main hypotheses emerging from the general principles discussed above – i.e., (i) the U-shaped effect of population-level homogeneity on exit rates, (ii) the dynamic trade-off between firm-level similarity and differentiation, and its effect on exit depending on the level of population-level homogeneity, and (iii) the inverted U-shaped impact of population-level homogeneity on new entrant's positional similarity.

Diversity-dependent exits

Following the first general principle that we derived from the theory presented in Figure 1, we expect a U-shaped effect of population-level organizational homogeneity on the exit rate of organizations. At low homogeneity, clustering of organizations in product space offers the opportunity to accumulate industry-wide information and knowledge, and to develop economies of standardization. In addition, convergence in product space increases legitimation of the form as it facilitates its social recognition in the wider community of stakeholders. As these positive externalities spill over to incumbents, while competition remains low, exit rates first decrease with population-level homogeneity. At high homogeneity, however, the impact of homogeneity on exit rates is reversed, because then competition dominates. Competition intensifies because similar organizations depend on the same pool of scarce resources. High population-level product homogeneity increases competitive pressures that counterbalance the benefits of similarity, ultimately increasing mortality. Thus, aggregate homogeneity first reduces exits due to increases in the pool of positive externalities, up to a point where competition raises organizational mortality again.

Hypothesis 1: Population-level homogeneity has a U-shaped effect on organizational exit rates.

The second general principle stemming from our theoretical model underscores the dynamic trade-off of firm-level similarity/differentiation: any effect of similarity on the focal organization's likelihood of exit is contingent on the degree of population-level homogeneity. Specifically, at low homogeneity, being similar to incumbent organizations enhances organizational survival by facilitating the spillover of positive externalities that result from population-level homogeneity. Under these conditions, the benefits of spillovers exceed the disadvantage of the competitive intensity associated with positional similarity. Conversely, an incumbent's likelihood of exit goes up with increasing dissimilarity from incumbents, as dissimilar organizations are unable to reap positive externalities. So, at low homogeneity, it is beneficial for the focal firm to be similar to incumbents. At high levels of homogeneity, however, differentiating away from incumbents reduces the negative consequences of crowding. In this case, the benefits of differentiation outweigh the drawback of foregoing the positive externalities resulting from similarity. The likelihood of exit is now positively correlated with the extent of focal firm similarity to incumbents. This leads to the following interaction effect of focal firm similarity and population-level homogeneity on the likelihood of exit.

Hypothesis 2: At low population-level homogeneity, focal firm similarity decreases the likelihood of exit, whereas at high population-level homogeneity, focal firm similarity increases the likelihood of exit.

Diversity-dependent entries

The second general principle of our theoretical model is also informative as to predicting the degree of entrant's similarity vis-à-vis incumbents. Increasing population-level organizational homogeneity first spurs new entrepreneurs to locate close to incumbent organizations in order to jump on the 'positive externalities bandwagon', up to a point where crowding takes over, forcing entrepreneurs to differentiate when entering a population. To evaluate entrepreneurial decision-making, however, we need to develop a theory that is able to link the aggregate macro processes of positive externalities and competition to the behavioral micro processes that drive an entrepreneur's decision concerning where to locate in resource space (cf. Ruef, 2005). Specifically, we need to answer a twofold question: to what extent and how do competition and positive externalities affect the choice of individual entrepreneurs with respect to their location in resource space?

Entrepreneurs are not fools rushing into organizational populations with their eyes blinded and their minds on hold (Aldrich and Fiol, 1994). Uncertainty, however, makes it hard for boundedly rational entrepreneurs to figure out which niche position will be particularly profitable. To cope with this uncertainty, entrepreneurs use market signals (Spence, 1973), and learn by observing and imitating other seemingly successful ventures (Delacroix and Rao, 1994; Cooper, Folta, and Woo, 1995). Indeed, institutional theorists argue that mimicry will be prevalent when uncertainty is high (DiMaggio and Powell, 1983). This is why nascent entrepreneurs will be sensitive to the behavior of their peers, particularly in industries where a scattered distribution of organizations in resource space – i.e., high diversity – increases uncertainty. Given the high risk of their ventures, entrepreneurs will jump on the bandwagon of any emerging dominant position to improve the viability of their ventures.[6] This choice not only facilitates the process of resource mobilization for the nascent entrepreneur, but also enhances legitimation and the accumulation of population-level 'common' assets. The latter will increase the survival chances of entrant entrepreneurs proximate to incumbents, reinforcing the homogeneity observed within the industry.[7]

When population-level organizational diversity decreases, though, so does uncertainty for the nascent entrepreneur. As a result, new entrepreneurs will be less inclined to imitate incumbents. After all, the emergence of a highly homogeneous distribution of organizations in product space will reduce the profit potential for further similar entrants. Rather, newcomers may seek to avoid the competitive downside of similarity by differentiating away from incumbents. Notice that our (weak) assumption is that entrepreneurs adopt simple decision heuristics that guide their search for opportunities to establish successful newcomer ventures. The assumption that entrepreneurial decision-making is at least intendedly rational is also underscored by Hannan and Freeman (1986: 63, emphasis in the original) who claim that "much of entrepreneurial activity involves <u>conscious revision of forms and routines</u> to take advantage of changing opportunities and constraints."[8]

Taken these arguments together, we expect that population-level homogeneity stimulates similar entries up to a point after which newcomers can avoid head-on competition with dominant incumbents by adopting differentiated positions.

Hypothesis 3: Population-level homogeneity has an inverted U-shaped effect on the similarity of new entrants vis-à-vis incumbents.

DATA, MEASUREMENT AND METHOD

Data

Our theoretical argument can be brought to the test with a data set that includes information about, at least, entries and exits, as well as the positions of organizations in resource space. Additionally, we need a measure of aggregate population-level diversity dynamics, as the latter is the benchmark against which we compare our key variables: positional similarity of entrants and exits vis-à-vis surviving incumbents. Moreover, additional controls are necessary to rule out competing explanations, such as those related to density dependence, geographical clustering and resource partitioning.

We test our hypotheses in the United Kingdom motorcycle industry. Figure 2 depicts the history of this paper's industry in terms of density of UK motorcycle producers.

[INSERT FIGURE 2 ABOUT HERE]

The data set used to generate Figure 2 includes 644 motorcycle producers during the period from 1895 to 1993. The main source of information is *British Motorcycles since 1900* (Collins, 1998), which includes the date of birth and disbanding of each firm in the UK. The information was refined by consulting *The Complete Illustrated Encyclopedia of the World's Motorcycles* (Tragatsch, 1977, 2000), which is considered to be the most reliable source for the industry, and the *Enciclopedia della*

Motocicletta (Wilson, 1996). Data at the product level were obtained from *The Register of Machines of the VMCC* (Hume, 1991). In order to test the reliability of the data, we checked the magazines of the period: *Motor Age* (from 1899), *Cycle Trade Journal* (from 1897) and *Motor* (from 1903) were consulted for this purpose. Finally, we cross-checked all the information with other references such as *A-Z of Motorcycle* (Brown, 1997), *Historic Motorcycles* (Burgess Wise, 1973), *The Ultimate Motorcycle Book* (Wilson, 1993) and *Encyclopedia of Motorcycling* (Bishop and Barrington, 1995). The year in which the first model of producer *x* was mentioned in the sources, was coded as the year of birth of this firm *x*, and the year in which firm *x*'s last model disappears from the sources' registers, was coded as its year of death.

Niches in the UK motorcycle industry

Following the studies on the automobile industry (Dobrev et al., 2001, 2002), we use the engine capacity (i.e., cc) of motorcycles as the major variable to map the positions of organizations in resource space. Although defining resource space with one (technological) dimension has limitations (see Dobrev et al., 2001), the approach allows one to make meaningful comparisons of firms over long periods of time. To be sure, engine capacity is an extremely important feature that defines niche segmentation in this industry, and it is a critical dimension along which competition and segmentation unfold. Given that the industry is straightforwardly organized around meaningful cc-niches and segments, engine capacity is highly suited to study blending and segregation processes. In the present study, we distinguish the following seven niches: up to 50cc, 51-125cc, 126-250cc, 251-350cc, 351-500cc, 501-600cc, and more than 600cc.

It is important to stress that these categories were not created by us, as researchers. Such a categorization has existed throughout the history of the industry, is well-established, and is widely used by stakeholders to classify motorcycle production in a systematic way. In fact, the above categorization can be regarded as an institutionalized convention, with specific cc-segments relating to specific semantic references. As a motorcycle industry historian reported to us (personal correspondence):

> "The categories were so well established and well known that nearly every book refers to them by name (e.g., 'Junior', for 350cc) rather than by capacity. I hadn't realized until I had to pull so many books from the shelf that the cc-categories were so well established that nearly all authors take for granted that the reader will know what capacity machine a 'Lightweight', etc. is."

The segmentation of the industry around these cc-classes emerged early in the industry's history, and remained remarkably stable since then. An important reason is that races and competition have always had a large impact on the development of the industry and the niches in which firms compete. Those races have been consistently structured around specific cc-classes, along which, eventually, demand boomed. According to an industry expert that we interviewed,

> "[a]s from 1949 the capacities for the classes were 125cc, 250cc, 350cc, 500cc and 600cc. These post-war categories were identical to pre-war, with the only change being to ban superchargers in an attempt to reduce costs. The 50cc-category was added to this set later. An often repeated saying amongst motorcycle distributors is: 'Race them on Sunday, sell them on Monday', meaning that people buy the motorcycles that they see win races. This was by far the major factor in determining engine size. Manufacturers made machines with capacities that coincided with racing categories (50cc, 125cc, 250cc, 350cc, 500cc, and 600cc and above)."

For tax purposes, some manufacturers produced motorcycles with an engine capacity that deviated from these 'fixed' classes – e.g., a 275cc-machine in 1909 could participate to the Six Days Scottish Trial in the 'Best solo between 250 and 350' category (Sandham, 1982). However, this was not the rule, but clearly the exception. For one, taxes were in fact based on either size or "horsepower", where the latter is a number typically calculated from engine-related factors such as bore, stroke, number of cylinders and the like. Often, the calculated "horsepower" had little to do with the actual horsepower (Koerner, 1995). In addition, for racing purposes such machines were not suited. Industry historians think that

> "it would be foolish for anyone to handicap themselves and not to take advantage of the full 350cc allowed. If a customer was in the market for a middle-capacity motorcycle, and a particular company had won the 350cc-championship, that's the bike the customer wanted, so he could tell his friends he had one 'just like the champion bike'. Then it would have been pointless for manufacturers to offer 275cc-bikes (other than for local taxation), since they couldn't race those bikes" (personal communication).

We do not claim that experimentation (e.g., the production of a 356cc-machine) did not take place over the history of the industry – it did, particularly in the early years. Rather we want to stress that the early development and institutionalization of standard cc-categories in the motorcycle industry de facto segmented the market into a few fixed cc-classes around which producers clustered and competed. The emergence of the official association of motor producers - The Cycle and Motor Cycle Association (CMCA, founded in 1899), exhibitions (The Stanley National Show in 1903) and competitions (the first of which was held in Richmond in 1897) all greatly contributed to the institutionalization of these categories. Nowadays, the above cc-categorization is taken-for-granted. The *Yearbook of Transport Statistics of Great Britain* (2005), for instance, follows a segmentation of the industry similar to the one we adopt here. The only exception is the split of the category 125-250 into three – i.e., 125-150cc, 150cc-200cc, and 200cc-250cc – in the *Yearbook*. Given the low frequencies observed within these categories – due to their late emergence – we decided to group them into a single segment.[9] The bottom line is that the categories we distinguish in this study quite sharply represent the boundaries of the niches and domains in which firms compete throughout the history of the industry. This gives us confidence that our cc-categorization correctly captures the niche-based processes of mutualism and competition among motorcycle producers.

Figure 3 shows the evolution of the proportion of densities in each cc-category over the history of the industry. It is worth mentioning that although the 50cc-category only emerged after WWII, this is not problematic as our aggregate measure of diversity is sensitive to the opening of new niches, as it should be (see below). Figure 3 reveals two key issues. First, the diverse cc-categories were populated by competitors as from the early years (an exception is, again, the 50cc-segment), which underscores the stability of the categories over time. Second, the peak of the industry (i.e., the most populated cc-segment) shifted 15 times over the period observed – i.e., eight times before the density peak in 1922, and seven times after 1922.

INSERT FIGURE 3 ABOUT HERE

One important reason for the early emergence of standard classes is that cc-categories differ significantly in terms of expertise, routines and investments required in the production process (e.g., the technological sophistication of high-capacity motorcycles is incomparable with that of scooters) and market segmentation (tailored at, e.g., 'elegant' ladies or macho-type customers like those advertised by the movie 'The Wild One'). Some authors even have claimed that, for instance, "scooters and motorcycles are so different in terms of both product architecture and manufacturing process that their belonging to the same industry could be put into discussion" (Corso, Muffatto, and Verganti, 1999: 159). Different products require different production processes, logistic procedures, pricing policies, marketing campaigns, et cetera. The case of Triumph is illustrative in this respect. At the time of the 1960s scooter craze, many British companies continued to make large-capacity motorcycles (often based on dated designs that no longer attracted customer interest). But the progressive polarization of the market stimulated some other producers to enter the small-capacity segment. When Triumph entered the small/medium range in 1959, it encountered several severe marketing problems as different distribution channels were needed for this type of products. The low quality of Triumph's Tigress scooter confirmed the difficulties on the production side. As some people used to say, a Tigress "was a joy to own so long as someone else was paying the repair bills" (Tragatsch, 2000: 48).

Altogether, this vignette points to what we claimed in the introduction: firms located in similar positions along the cc-classification axis are more likely to possess comparable blueprints and, thus, to compete for similar resources. Dobrev et al. (2001) recognized a similar duality between positions and competencies in a related industry (i.e., automobile). As they concluded, "the choice of engine capacity made by automobile producers over the years proves to be revealing not only of the ranges of their technological offerings but also of these firms' strategies in product marketing and competitive pricing, customer segment targeting, supply-chain management, and innovation" (Dobrev et al., 2001: 1315). Following their lead, we used information on cc-positions to identify any producer's location in resource space, to map the similarity of entries and exits vis-à-vis the industry's incumbents, and to develop a measure of population-level organizational diversity below.[10]

Measurement

<u>Dependent variables</u>

To test Hypotheses 1 and 2, in line with a long list of longitudinal studies, we used <u>Organizational Mortality</u> as the dependent variable. Exit events usually associated with the ending of an organization's history are disbanding, exit to another industry, and a merger or acquisition. Failure is being defined as disbanding or exit to another industry. It is, however, not reasonable to assume that mergers and acquisitions represent instances of failures, as these events might happen for divers reasons. Those firms known to have ended by a merger or an acquisition were therefore treated as right-censored observations, a standard practice in organizational ecology studies. While our data sources were clear about disbanding, they did not always report exactly what happened to some firms when they dropped from the set of producers for other reasons. Eight percent of the cases could not be exactly classified. This appeared to be especially the case for motorcycle firms with short longevity. As our reading of the history of the industry indicates that most of these 'unknown events' were in all likelihood disbandings or exits to other industries, we coded them as failure events. Note that Hannan, Carroll, Dobrev, and Han (1998a, 1998b) and Dobrev et al. (2001) used the same procedure in the automobile industry.[11] Thus, following previous practice, our dependent variable is "disbanding/exit to another industry, defined to include events of unknown type" (Dobrev et al., 2001: 1311; see also Hannan et al*.*, 1998a). In coding the entry and the exit events, we followed the recommendation of Petersen (1991) and marked the event at the midpoint of the year.

Our second dependent variable, used to test Hypothesis 3, should account for the degree of similarity among motorcycle producers. In our empirical setting, a meaningful measure of new entrants' similarity vis-à-vis established incumbents could be developed on the basis of the focal firm's relative position in the population's resource space. As explained above, we adopted a common segmentation of the market across seven engine power niches: up to 50cc, 51-125cc, 126-250cc, 251-350cc, 351-500cc, 501-600cc, and more than 600cc. We subsequently assessed entrant-incumbent similarity or niche overlap by counting the number of incumbents present in the focal entrant's niche.[12] Such an overlap density measure has also been used in the automobile studies (Dobrev et al., 2001, 2002). Building on Baum and Korn (1996) and Barnett and McKendrick (2001), we expressed this variable as the sum of the overlap between each potential pair proportionally to their overlapping product range. Notice that this measure allows for asymmetric competition between pairs. Consider, for instance, firm A producing 125, 250 and 350cc-motorcycles, and firm B that is active in the 350cc-segment only. If firm A is the focal firm, niche overlap density is 1/3, as the former is only 1/3 similar to the other. In contrast, firm A's niche fully overlaps firm B's niche. Therefore, if firm B is the focal firm, overlap density is 1. Suppose firm B enters the 600cc-segment the year after. In this case, firm A is still 1/3 similar to the second, but firm B's overlap with A now decreases from 1 to 1/2 as B is now 1/2 similar to A. If both firms exactly occupy the same niches, a value of 1 is given to both rivals. To test our Hypothesis 3, such a <u>Niche Overlap</u> measure was computed for the year of entry of each firm. This niche overlap measure was also computed for all the years in which the focal firm survived, and then used as an independent variable in the exit analysis (see Hypotheses 1 & 2).

An alternative solution to operationalize our construct would have been to calculate this measure as the Euclidean distance with respect to engine capacity (e.g., Baum and Haveman, 1997). This is empirically feasible as our technological resource space is defined by a graded metric (600cc, for instance, is larger than 250cc). In the present case, however, we believe that niche overlap represents a more appropriate indicator of organizational similarity for theoretical reasons. First, it would be incorrect to say, for instance, that the competitive intensity between firms linearly depends on the distance in cc-space. As explained above, the cc-categories we distinguish can be considered to be the 'natural' boundaries of the niches and domains in which firms compete. As a result, a new 750 cc-entrant, for instance, does not necessarily put more pressure on a 250cc compared to a 125cc-producer. Second, it should be recognized that our theory aims at modeling the dynamics of niche <u>positions</u> at both the firm and the population level, and not so much those of the distances between niches. It assumes that it is the relative frequencies of firms in different niches per se that determine where newcomers enter and which incumbents survive. We predict, for example, that crowding of specific niches eventually leads to entry in relatively empty niches, but not necessarily in more distant niches (for a similar justification, see also Dobrev et al., 2002; Barnett and McKendrick, 2004).

Independent variables

Our multi-level niche-overlap hypotheses underscore the effect of the aggregate distribution of firms in product space (i.e., population-level organizational diversity / homogeneity) in shaping both the similarity of new entrants vis-à-vis incumbents as well as the impact of the focal incumbent's similarity on mortality. The measurement of aggregate diversity has a long tradition in several disciplines such as biology, economics and sociology. Especially the work of biologists is insightful for our purpose, given the analogy between the way we envision organizational diversity and the conceptualization of biological diversity. Biological diversity can be partitioned into two components: species richness and evenness (Simpson, 1949; Magurran, 2003). Diversity is considered to be high when a habitat has a lot of species (i.e., richness) and low variance in species abundance (i.e., similarity of population sizes or so-called evenness). Obviously, a conception of diversity consisting of both evenness and richness is intuitively appealing in the context of the world of organizations, too.

Many biologists have tried to develop diversity indices – single statistics that incorporate information on richness and evenness, a blend that is often referred to as heterogeneity (Magurran, 2003). Magurran (2003: 115), summarizing and comparing the behavior of many different diversity indices, concludes that the often-used Simpson index is one of the most meaningful and robust diversity measures available. This index is defined as

$$SI = \sum p_i^2,$$

where p_i is the proportion of individuals in the ith species. This measure takes into account both richness and evenness. It ranges between 0 (number of species going to infinity with equal population size) and 1 (one dominant species). Note that this measure thus maps the degree of dominance within a population – i.e., the converse of diversity. The same measure is known in economics as the Hirschmann-Herfindahl index, where it is successfully used to measure firm size concentration (Nissan and Caveny, 2005). In sociology, the measure is known as the Blau index of heterogeneity/homogeneity, suggested by Blau (1977: 276) to measure structural differentiation in social systems. It has, for instance, extensively been applied to assess demographic diversity of members of (top management) teams in organizations (e.g., Boone, van Olffen, van Witteloostuijn, and De Brabander, 2004), as well as by Wezel and van Witteloostuijn (2006) in their study of the role of scale and scope economies in interaction with population-level crowding.

Given the quality of the index, we apply it in the present study to the distribution of motorcycle firms over seven cc-categories to assess Population-Level Homogeneity. We measured the homogeneity of the supply of products in the market by calculating the proportion of producers located in each cc-segment and subsequently summing the squared proportions. As the number of cc-categories is fixed to seven in this case, the minimum value equals .14 (i.e., $7 * (1/7)^2$, implying maximum heterogeneity or diversity). To clarify the intuition behind this measure, we calculated some examples in Table 1.

[INSERT TABLE 1 ABOUT HERE]

Comparing Examples 1 and 2 shows that the index decreases (more diversity) when more variety is offered to the market (i.e., richness), keeping evenness constant.

Examples 3 and 4 make clear that when entrepreneurs open up small niches, the index decreases, implying more diversity. Note in this respect that the index correctly captures the opening of the 'up to 50cc'-category after WWII, as empty niches do not affect the *SI*, whereas the addition of non-empty niches does. Taken together, most would agree that population-level diversity is lowest in Example 3 (two dominant forms), followed by Example 4 (two dominant forms with two small niches), and Examples 1 and 2, the latter showing the most robust diversity (higher richness and evenness).

The *SI* has potential drawbacks, too, however. First, because proportions are squared, more weight is given to large niches at the expense of small niches. Notwithstanding this bias, though, the measure does behave as it should (i.e., it decreases) when small niches are opened up (see Examples 3 and 4 in Table 1). To be on the safe side, though, we re-did all our analyses with a number of alternative measures – i.e., the squared root of the *SI*, the reverse of the Jacquemin-Berry entropy measure (i.e., $1-\sum p_i * log(1/p_i)$) and the squared root of this measure, which all are supposed to be less sensitive to the largeness of the dominant segment than the *SI* (Magurran, 2003). All these robustness checks (available upon request) produced similar findings. This is not surprising, given the high correlation among the alternative measures and the *SI* (all above .9).

Second, some authors argue that the *SI* measure does not account for the niche-specific probability of entries. Although more complicated solutions are available, the addition in the exit analysis of a time-varying set of dummies accounting for the cc-categories in which each firm is involved is meant to control for this potential bias (see below). Incidentally, this procedure allows us also to control for any unmeasured structural differences between niches, and for the fact that the 'up to 50cc'-segment appeared much later than the others. Third, given the non-parametric nature of the measure, it does not take into account the distance between different categories (e.g., the genetic distance between species in biology or the distance between cc-segments in the present case). In some cases, this can be considered to be a drawback. However, as explained above when introducing the firm-level overlap measure, theoretical reasons made us conclude that the *SI* (which is based on overlap and similarity) is most suited for testing our theory in the motorcycle industry context.

In the exit analyses, the linear and squared terms of the *SI* were used to test for Hypothesis 1's U-shaped prediction of the effect of population-level homogeneity on organizational exit rates. An interaction of each focal firm's niche overlap measure (described above) with the *SI* and its squared term, Niche Overlap * Population-Level Homogeneity and Niche Overlap * Population-Level Homogeneity^2, was used to test Hypothesis 2. In the entry analyses, Hypothesis 3's inversely U-shaped effect of population-level homogeneity in molding entrants' similarity was tested by entering the linear and squared term of *SI*. Of course, for the entry analysis, we excluded the focal entrant when computing this *SI*. Figure 4 presents the pattern over time of our *SI* measure of population-level homogeneity for the exit rate analysis.[13]

[INSERT FIGURE 4 ABOUT HERE]

Control variables

To rule out several alternative explanations, we added a few control variables. Organizations can enter an industry following different paths. Previous research on the American automobile industry (Carroll, Bigelow, Seidel, and Tsai, 1996) found that the life chances of lateral entrants were higher than of those entering de novo. Following Dobrev, Kim, and Solari (2004), we introduced three dummy variables to code different entry modes: DeNovo organizations with no experience of any kind (which is the reference category), DeAlio lateral entrants from other industries, and DeIpso firms that either entered through a merger or reflect re-entry of motorcycle manufacturers. The age of an organization is measured as the tenure of the firm in the industry. Unfortunately, the archival sources we used contain only the year of the event. As before, we followed Petersen's (1991) advice, benchmarking organizational Age from the midpoint of the year of entry.

We controlled for the negative impact of firm size on organizational mortality by creating a time-varying variable counting the number of plants owned by the focal firm – Size. Due to our data set's century-long time window, we were unable to collect conventional size measures. The number of plants is a sensible surrogate measure, though. For instance, two studies of Mata and Portugal (1994, 2000) reveal a strong positive and statistically significant correlation between number of plants and standard size measures (e.g., number of employees). We logged this measure to reduce its variance. As being involved in multiple niches (or classes) may affect our measure of similarity, we control for the technological scope of the focal firm by computing its Niche Width, measured as the range of the engine capacity in cc across the models the organization produced in any given year. Organizations with broad (narrow) niches can be considered to be generalists (specialists) (see Dobrev et al., 2001, 2002). In the exit analysis, we also used niche fixed effects to rule out any cc-segment specific pattern. Any potential mismatch between organizational position and market structure was controlled for by a time-varying dummy variable coded as 1 – With Peak – when the organization is located in the market center, defined as the cc-category with the largest density. This allows us to rule out the simple explanation that being in the center is what matters in this industry.

As far as industry-level controls are concerned, we include the well-established density measures. We counted Density as the number of incumbent UK motorcycle producers in each year *t*. To capture the effects of competition on founding and mortality, we added $Density^2$. To rule out any potential effect of scale economies on entry, exit and diversity, we compute a variable named Average Scale, defined as the yearly number of motorcycle sales divided by the total number of incumbent organizations in the industry. After controlling for the log of Total Motorcycle Sales (which accounts for time-varying changes in the carrying capacity of the population), we interpret the Average Scale measure as a proxy for expected concentration and as a control for resource partitioning dynamics. Specifically, in the entry analyses rising Average Scale should go hand in hand with lower overlap of new entrants. In the exit analyses, following Dobrev et al. (2001), we interact focal firm's Niche Width with Average Scale to check whether specialist survival increases with concentration.[14]

Moreover, the British motorcycle industry had a dominant production area in the geographic triangle between the cities of Birmingham, Coventry and Wolverhampton. Almost half (278 out of 639) of all manufacturers, including Ariel, BSA, (Royal) Enfield, Norton and Triumph, were located there. To control for any network effect, we created a dummy variable District to identify those organizations that have their headquarters in that area. To control for the general economic climate and for latent demand for transportation, we created a time-varying variable measuring the gross domestic product per person – GDP per Person – using data obtained from Mitchell (1998). Furthermore, three dummies were constructed to control for the influence of WWI, WWII and the beginning of the Japanese era – Post-1958. Tables 2 and 3 present the descriptive statistics and correlations of the variables.

[INSERT TABLES 2 AND 3 ABOUT HERE]

Method

The final data set includes 644 entries and 598 exits, implying 4,685 firm-year observations. For the survival analysis, we divided the life of each producer in organization-years through the spell-splitting technique (Allison, 1984; Tuma and Hannan, 1984). Different time functions and different covariates can be used to model the hazard rate of each organization. We model the rate at which failure events occur at a particular time, *t*, conditional upon the values of the observed covariates and upon the event not having occurred prior to time *t*. This rate, $r[t|X(t)]$, is generally known as the hazard rate. It is formally defined as

$$r(t \mid X[t]) = \lim_{\Delta t \to 0} \frac{\Pr(t + \Delta t > T \geq t \mid T \geq t)}{\Delta t}.$$

A log-linear function is used to relate observed covariates, $X(t)$, to the hazard rate. To allow the baseline hazard rates of the different producers to vary in an unrestricted fashion, we modeled this rate according to a piecewise exponential formulation. More precisely, the age of an organization is divided into intervals, and the hazard is constant within each interval but can vary across intervals. We define a set of J intervals, dividing the age variable at precise points (a_1, a_2, a_3, a_4,…, a_j), where $a_0 = 0$ and $a_j = \infty$. The interval J is given by $[a_{j-1}, a_j)$, and the hazard of the firm i is defined by

$$r(t) = \mu_j \exp[\beta' x], \quad \text{per} \quad a_{j-1} \leq a < a_j,$$

where $\alpha_j = \log \mu_j$. This formulation allows the intercept of the log-hazard function to vary at different cut-off points. After examining life tables, we divided firm age in the following six segments: Age 0-1 (0.5-1 years), Age 1-2 [1-2 years), Age 2-3 [2-3 years), Age 3-6 [3-6 years), Age 6-10 [6-10 years) and Age 10-∞ (10-onward years).

To estimate the hazard rate (r) for organization i, we modeled it as a function of a set of tenure-specific effects (a), a vector of firm's characteristics (X) and a vector of environmental variables (V). That is,

$$r_i(u) = \mu_j(a) \exp(X_{ia}'\alpha + V_t'\beta).$$

As for the entry analysis, we recurred to the Generalized Estimating Equations (GEE) method to model entrant niche overlap. GEE is particularly suited to control for potential autocorrelation resulting from the clustering of entry events at the year level. The GEE methods requires a specification of a working correlation matrix. The exchangeable correlation structure – i.e., assuming equal auto-correlation among the years – was found to fit our data best. Because the observations within years cannot be assumed to be independent, we also report robust standard errors, using the sandwich estimators developed by Huber (1967) and White (1980). Notice that this procedure gives valid standard errors even if the within-group correlation is not as hypothesized. We log-transformed the dependent variable to adjust for its skewed distribution. Ignoring the controls, for the sake of brevity, the model becomes

$$Log(NicheOverlap_i) = \exp[\beta_0 + \beta_1(Density) + \beta_2(Density^2) + \\ + \beta_3(Population - Level\_Homogeneity) + \beta_4(Population - Level\_Homogeneity^2)] + \delta\varepsilon_i.$$

All the estimates were obtained using the software package STATA 9.

EMPIRICAL RESULTS

Table 4 presents the maximum likelihood estimates of the piecewise exponential model of mortality rates for 644 producers during the period 1895-1993. Model 1 is a baseline model containing control and density variables. Model 2 adds a test for resource partitioning processes in this setting. Model 3 includes the estimates of the population-level homogeneity main effect through its linear and squared term. Finally, Model 4 adds the interactions of niche overlap with the linear and squared population-level homogeneity measures.

[INSERT TABLE 4 ABOUT HERE]

The estimates of the control variables presented in Model 1 are largely in line with our expectations. WWII, but not WWI, positively affected the failure rates of motorcycle producers. After the 'golden age', in fact, the UK industry suffered a massive flop: between 1929 and 1938, the overall production level dropped from 147,000 to 58,000 units and reached the minimum level of 1,600 in 1945 (Koerner, 1995). Larger firms are exposed to a lower risk of mortality compared to their smaller counterparts, as it is clear from the Size estimate. In a similar vein, being located in the center of the market – With Peak – provides a survival advantage, significantly reducing the risk of failure by about 34 per cent [exp(-.40)]. The piecewise model specification sheds light on the complexity of the relationship between Age and mortality. Furthermore, the effect of prior experience inside the same industry – De Ipso – or other sectors – DeAlio – is negatively and significantly related to the exit rate (the omitted benchmark category is DeNovo). The negative and significant coefficient of the District variable suggests that location matters in this industry. The hazard of failure for firms located in the Birmingham-Coventry-Wolverhampton district is reduced by about 28 per cent [exp(-.33)] compared to those located in other parts of Great Britain. Generalists organizations benefit from lower failure rates, as the estimate of the Niche Width coefficient suggests. Average Scale exhibits a positive and significant effect on failure rates.

The competitive effect due to organizational similarity is mirrored in the significant and positive coefficient of the Niche Overlap variable. At the mean value of organizational similarity, the probability of failure of the focal organization increases by about 87 per cent [exp(44.4*.016)].[15] Although the latter finding is consistent with several ecological results, we predict this average effect to greatly vary according to the degree of population-level homogeneity. Notice that adding this variable does not cancel out the diffuse competition and legitimation effects. As the coefficients obtained for <u>Density</u> and <u>Density</u>^{2} show, mortality is negatively related to density up to a certain point (i.e., 63), after which this relationship becomes positive.

Model 2 includes the standard resource partitioning interaction between concentration (<u>Average Scale</u>) and niche width (<u>Niche Width</u>*<u>Average Scale</u>). It shows that generalists (i.e., broad portfolio producers) in this industry enjoyed greater survival benefits at increasing average scale. This finding runs against resource partitioning research (e.g., Dobrev et al., 2001) and suggests that this industry was not affected by scale-induced partitioning. Two reasons can be offered for this. First, the British motorcycle producers apparently were not able to reap the opportunities offered by scale economies. Incidentally, this was the key disadvantage of British producers compared to Japanese ones (Boston Consulting Group, 1975: 53, Exhibit 21). As the BCG report (1975: XI, XIII & 52) comments,

> "The disastrous commercial performance of the British manufacturers … is the final result of their failure to respond effectively to the strategic implications of the economic relationship between volume and costs in the motorcycle industry … Because the British [motorcycle] producers purchase in small volumes, their suppliers cannot themselves use the lowest cost methods … The Japanese are much larger in both cumulative experience and current volume than the British industry. This has resulted in a massive disparity in cost effectiveness between the two."

Second, generalists appear to be larger than specialists, on average (see descriptives in Table 2), which might be associated with differences in cost effectiveness between both organizational forms not captured by our models. We, therefore, speculate that at least part of the negative effect of niche width on failure rates at high <u>Average Scale</u> might be the result of such differences.

As far as Hypothesis 1 is concerned, the addition of the (non-linear) main effect of Population-Level Homogeneity (Model 2) significantly improves the fit of our model to the data ($\chi^2[L_2 | L_1] = 19.32$ with 2 d.f. and $p < .05$). The U-shaped effect of Population-Level Homogeneity on mortality (similar to that of density) reaches its minimum within the range observed, providing support to Hypothesis 1. In particular, as population-level homogeneity increases from 0.14 to 0.28, the organizational failure rate decreases by about twenty per cent vis-à-vis the rate at the minimum of population-level homogeneity. Above this point, the organizational risk of mortality starts augmenting, reaching a seven-fold increase at the maximum value observed in our sample. As Hypothesis 2 suggested, the trade-off between similarity and differentiation is inherently dynamic and contingent on the aggregate distribution of organizations in the population: both the coefficients of the interaction terms are significant and indicate a potential U-shaped effect. The estimates obtained in Model 3 for the interactions Niche Overlap* Population-Level Homogeneity and Niche Overlap* Population-Level Homogeneity^2 support our argument: as population-level organizational homogeneity increases, the effect of organizational similarity on mortality turns from negative to positive. We plotted three curves in Figure 5.

[INSERT FIGURE 5 ABOUT HERE]

The curves reflect the multiplier of the interaction effect of the Population-Level Homogeneity and Niche Overlap measures, and illustrates the impact of Niche Overlap on the failure rate of motorcycle producers at different levels of population-level homogeneity – i.e., at the mean (.21), at the mean plus one standard deviation (.25), and at the mean minus one standard deviation (.17). On the *x*-axis, the complete range of observed values for our Niche Overlap variable is considered. The plots provide strong support for Hypothesis 2. More specifically, niche overlap decreases organizational mortality when Population-Level Homogeneity is low. However, when Population-Level Homogeneity is high, niche overlap increases mortality. Consider, for instance, the impact of average niche overlap (44.42) at different values of population-level homogeneity: whereas this level of organizational similarity increases survival at low and medium levels of *SI* (multiplier of the failure rate=0.69 and 0.75, respectively), it augments organizational mortality (multiplier of the failure rate=2.25) at high levels of population-level homogeneity. Consistently with our hypothesis, increasing values of niche overlap magnify this trend of results – see Figure 5.

These results present only one side of the coin, namely the exit side. Table 5 presents the GEE estimates of the model of niche overlap for 644 entrant motorcycle producers in the United Kingdom during the 1895-1993 period. Model 1 contains control variables. Model 2 adds the density measures. Model 3 presents the estimates of the full model specification after including the population-level homogeneity (*SI* and SI^2) variables.

[INSERT TABLE 5 ABOUT HERE]

The estimates of the control variables suggest that the degree of similarity of new entrants decreased during periods of tough competition as in the Post-1958 Japanese era. Increasing gross domestic product per person – GDP per Person, a proxy for latent demand – boosts organizational diversity by reducing new entrants' niche overlap. The coefficient of the variable District, albeit unstable, seems to points to a tendency towards increased similarity within the Coventry-Birmingham-Wolverhampton agglomeration. The width of a new entrant's niche (Niche Width) positively and significantly increases similarity. Furthermore, firms entering from a different industry (i.e., DeAlio) exhibit a significantly lower degree of niche overlap compared to inexperienced organizations (i.e., DeNovo). According to Model 1, Average Scale exhibited by the industry decreases the degree of overlap of new entrants, which is consistent with resource partitioning theory. However, this effect disappears when density and homogeneity are entered in the equation (Models 2 and 3). Taking entry and exit findings together suggest that 'standard' resource partitioning is probably hardly at play in the present setting.

Model 2 reveals that increasing Density has a positive impact on the new entrant's niche overlap with incumbents up to a point (i.e., 123), above which new entrants will differentiate away from incumbents ($Density^2$). As far as Hypothesis 3 is concerned, the inverted U-shaped effect of Population-Level Homogeneity on new entrants' similarity is confirmed. At low levels of *SI*, new entrants augment their similarity to incumbents. At high levels of Population-Level Homogeneity, however, the reverse relationship holds true: new entrants reduce their niche overlap with incumbents. In Model 3's specification, maximum similarity is observed when Population-Level Homogeneity is at a value of .28. To be more precise, as population-level homogeneity reaches this value, organizational similarity increases by about 1.5 times vis-à-vis the rate at the minimum of population-level homogeneity. Above this value, similarity starts declining, suggesting an increase in organizational differentiation.[16]

ORGANIZATIONAL CHANGE

Our analyses provide evidence as to the importance of competitive positions for organizational survival. They, however, remain silent about how organizations come to occupy these positions in product space. This raises an important macro-level question: to what extent are the dynamics of the distribution of organizations over niches driven by environmental selection (via the replacement of unfit incumbents by new entrants) versus organization-level adaptation (through incumbents changing positions)? Note that our theory in principle allows for both mechanisms. Referring to Figure 1, imitation and differentiation might relate to new entrepreneurs replacing unfit incumbents, or incumbents changing their position in resource space to improve their fit. Thus, population-level diversity can change as a result of the differential selection pressures on organizations occupying different positions in resource space, as well as of positional changes by incumbents.

Based on relative and structural inertia theory (Hannan and Freeman, 1984) ecologists would argue that selection is the most important mechanism behind diversity evolution. Given the strong link between niche positions and organizational blueprints in the current setting, we believe that inertia could prevent firm-level adaptation. However, one cannot exclude the possibility that incumbent organizations try to fine-tune their location in resource space as a function of the dynamic trade-off discussed above. Indeed, several scholars stressed that models of population dynamics should not ignore the adaptive force of organizational (here positional) change (Fombrun, 1988; Mezias and Lant, 1994). To explore this assertion we ran three additional models.

First, if inertia is important, one would expect that incumbents, compared to new entrants, cannot respond as swiftly to opportunities and threats that result from variations in population-level diversity. Similarly, given their history, organizations that happen to be in a ‘wrong’ position (e.g., an overly crowded niche) will have a hard time to switch to relatively empty niches. The result is that, on average, the likelihood of change will be loosely coupled with population-level diversity.

[INSERT TABLE 6 ABOUT HERE]

The dependent variable in the first model in Table 6 is Niche Center Change. For the coding we follow Dobrev et al. (2001), and defined a change in the market position of the focal firm as a shift in the center of the producer's technological niche by more than ten per cent. The estimates reveal that niche center change is not affected by the interaction of population-level homogeneity with firm-level niche overlap.[17] So, consistently with an inertia argument, organizations do not seem to use population-level diversity relative to their position in resource space as a map for change, although the same variables do affect exits.

Second, organizational ecology's inertia theory argues that organizations changing their core features suffer from a liability of newness that raises their hazard rate (Amburgey, Kelly, and Barnett, 1993). The second model in Table 6 presents the estimates of a piecewise exponential exit rate model with a dummy variable flagging the presence of a niche center change included. In line with Dobrev et al. (2002), we interpret the positive and significant coefficient of this variable as supporting the inertia argument: positional changes are apparently associated with significant process losses (Hannan and Freeman, 1984).

Third, on a macro level, given the above findings, we expect entries and exits to be more relevant than incumbents' changes in predicting the dynamics of industry-level homogeneity. The third model in Table 6 presents the estimates of a regression using absolute change in the *SI* measure – *SI* Absolute Change – as the dependent variable.[18] The number of births and deaths are inserted as covariates, together with the sum of the yearly niche center changes observed in the industry, and density and density squared. Only entries and exits appear to affect changes in population-level diversity. Altogether we interpret the findings of these three models as being consistent with structural inertia theory, pointing to selection – more than to adaptation – as a key driver of population-level diversity (Hannan and Freeman, 1984).

APPRAISAL

This paper sought to contribute to the literature about the dynamics of organizational diversity. Following a logic similar to density dependence, we developed a diversity-dependence theory that elaborates on the evolution of the distribution of organizations in product space. In so doing, largely inspired by Hawley's work (1950), we integrated insights from different theory fragments (i.e., Carroll, 1985; McPherson, 1983). Starting from the assumption of organizational diversity as stemming from positional differences in product space, we tested our hypotheses in the British motorcycle industry. The findings obtained confirm our theory. Population-level diversity shapes the position that entrepreneurs will adopt and the position of the incumbent firms that survive in predictable ways, reinforcing the dynamics of population-level organizational diversity.

As predicted, we found that when industry diversity is high, rising industry-level homogeneity increases the mortality of the incumbent firms that populate isolated niches and, at the same time, spurs entrants to locate close to incumbents. This pattern of exit and entry, of course, reinforces the homogenization of the industry. We invoked spillover effects resulting from positive externalities, inducing benefits of crowding, as the underlying drivers of this process. However, when population-level homogeneity increases further, competition undermines the benefits of crowding. The result is that the life chances of isolated incumbents with low niche overlap are enhanced and that new entrants try to spot isolated niches with low competitive pressure. This reversed pattern renews population-level organizational diversity.

Our findings contribute to the existing literature in several ways. For one, the theory we present is inspired by organizational ecology's density-dependence logic. Similar to density dependence, it is an endogenous theory where the firm-level outcome variables of interest (i.e., firm-level niche position and exit) depend on the aggregate level of the outcome variable in the system (i.e., the distribution of firms over niche positions). That is, we propose a theory of population-level diversity dependence which is complementary to density-dependence theory. However, whereas the density-dependence argument focuses on understanding the dynamics of the number of firms, our theory deals with the positional dynamics of a given number of organizations in resource space. By doing so, we follow the plea of Freeman and Audia (2006) to relax the assumption of organizational homogeneity (as in density-dependence theory) to fully account for diversity in organizational populations.

A second related theory fragment is resource partitioning (Carroll, 1985). Again, there are similarities with certain parts of our theory. First, the negative feedback loop that illustrates how crowding leads to differentiation is central to resource partitioning processes, too. Specialist organizations thrive exactly because of crowding among generalist organizations. Again, however, our theory adds to this crowding logic by spelling out alternative mechanisms behind the emergence of convergence. That is, we suggest that organizational differentiation does not only result from increasing <u>market share</u> concentration, but can also be triggered by concentration in <u>product space</u> due to forces of commensalism, independently from scale economies. In this respect, we believe that resource partitioning may be viewed as a particular case of differentiation resulting from crowding. Notice also that our theory, unlike the predictions of Carroll (1985) on the sustainable bifurcation between generalists and specialists in populations, accommodates for cyclical patterns of diversity: differentiation may induce a new cycle of imitation that may last until competition takes over, again.

Third, our theory contributes to the literature on differentiation strategies. Traditionally, the strategy approach to differentiation is rather static, arguing that an organization's 'optimal' (i.e., performance-maximizing) position in product space depends upon the industry's market structure, particularly the distribution of rivals across product space in combination with the location of demand (Boone and van Witteloostuijn, 2004; van Witteloostuijn and Boone, 2006). For example, Deephouse (1999: 148) suggests an optimal intermediate level of differentiation / similarity in his integrative theory of strategic balance, producing the "main recommendation that firms seeking competitive advantage should be as different as legitimately possible" after balancing "the benefits of reduced competition against the costs of reduced legitimacy." In the current paper, we develop a similar trade-off logic, following Baum and Haveman (1997), but add an emphasisis on the dynamic nature of the balancing act. In a similar vein, Boone et al. (2004) offer a dynamic theory of differentiation strategies in the context of a resource partitioning framework. In the present paper, we suggest a more general dynamic theory of organizational differentiation / similarity in which the 'optimal' product position is a moving target, changing endogenously over time with shifts in population-level organizational diversity.

A final remark relates to Wezel and van Witteloostuijn's (2006) recent study of the British motorcycle industry. There, the logic as to the non-linear effect of population-level homogeneity developed above is applied in a different and more limited theoretical context. That is, they study the impact on organizational mortality of scale and scope economies in interaction with crowding, arguing that increasing population-level homogeneity rewards broad niche incumbents. In the present paper, we move beyond their rather static approach by developing a comprehensive dynamic theory of diversity dependence (on the antecedents and consequences of organizational conduct), focusing on the interplay between firm-level similarity and population-level homogeneity, and dealing with organizational mortality and founding. Interestingly, additional mortality analyses (available upon request) show that the survival benefits of broad niche strategies in crowded markets, as suggested by Wezel and van Witteloostuijn (2006), disappear when added to our complete model specification, whilst the results reported above are retained. We interpret this finding as support for our plea for a more general dynamic theory of organizational similarity and diversity dependence.

Our study is not without limitations, which suggest important avenues for future research. First, a key issue relates to the definition of population-level homogeneity. In the present study, we focused on the organization's product portfolio in technological space as the crucial dimension of diversity. Although we trust the matching between this measure and the theoretical construct advanced here (see also methods section for a discussion), future research is needed to test whether or not our overall logic applies to other dimensions of organizational diversity. For example, organizations may also differ in terms of their style of human resource management (e.g., Baron, Burton, and Hannan, 1999) and geographical location (e.g., Baum and Haveman, 1997). It would be interesting to find out whether the type of evolution of population-level organization diversity is dimension-dependent – be it linearly decreasing (institutional theory), linearly increasing (resource partitioning) or non-linear (this paper) –, how different dimensions interact in producing population-level diversity, and how the type of evolution relates to several contingencies.

Related to the above, an obvious alternative explanation for the present findings, given the existence of a geographical agglomeration within this industry, is that the blending and segregating forces behind our diversity-dependence theory may be especially at work within the Coventry-Birmingham-Wolverhampton (henceforth CBW) district. If this holds true, then the two dimensions of geographical and product clustering are likely to collapse into a single one, implying that the geographical agglomeration of the industry is responsible for the findings reported above. We double-checked this hypothesis by running models of entries and exits for the sub-sample of firms operating within the CBW district, comparing the results with those obtained from the sub-sample of organizations located outside CBW (available upon request). All the variables of theoretical interest such as density, *SI* and niche overlap were re-computed at the local level. The estimates obtained demonstrate that our theory holds true both inside and outside the geographical agglomeration. In the case of exit rates, the theory seems to work slightly better outside the CBW region. In the entry case, the main findings appear to remain unaffected by the geographical split of the data set. We interpret these results as suggesting that the influence of geographical agglomeration on the results reported is limited, which underscores the relative independence of geographical and product-based clustering in this industry.

Second, one might also wonder how our theory and findings depend on the mere passage of time. Specifically, organizations might become increasingly similar initially, concluding an experimental phase in which they seek for a 'dominant design', after which competitive forces trigger increasing dissimilarity, again (cf. Anderson and Tushman, 1990). This is an alternative argument suggesting a non-linear evolution of population-level organizational diversity. This alternative explanation may be ruled out by controlling for the influence of industry age and industry age squared. Therefore, we re-ran all our entry analyses after controlling for the time elapsed since 1895 and its square (again, the results are available upon request). As the estimates demonstrate, our findings remain unaffected by the addition of these further controls. Additionally, we re-did the exit analyses with industry age and industry age squared included, as well as their interactions with niche overlap. These additional interactions are not significant (available upon request, too). By showing the lack of influence of these industry age-related variables, we are able to exclude the mere passage of time as an alternative explanation for our key findings.

Finally, consider that in this industry the peak of the market (i.e., the most densely populated segment) shifted several times (i.e., eight times before the density peak, in 1922, and seven times after this year). This implies the manifestation of what we may call 'dancing peaks', acting as moving targets for organizational (re)positioning behavior. Following our rationale, the positive feedback loop presented in Figure 1 generates the emergence of a market peak in which firms enjoy positive externalities across organizations. As this process unfolds, niches get crowded and competitive intensity spurs the differentiation of new entrants and incumbents, reflecting the negative feedback loop of Figure 1. This process of endogenous differentiation may result in an emerging dominant form, attracting other organizations. Hence, a new positive feedback cycle of imitation starts until competition will take over again. In other words, a bi-directional link between differentiation and imitation produces the cyclical dynamics of our diversity-dependence theory.

So, the theory proposed here suggests that population-level organizational diversity is likely to follow a cyclical pattern in which periods of homogenization are followed by periods of increasing diversity, and vice versa. It is clear, however, that in order to establish the extent to which the micro processes of entry and exit we suggest are related to the dynamics of aggregate population-level organizational diversity, more in-depth research is needed in other empirical settings. Our theory may be used to interpret the heterogeneous trajectories of product diversity exhibited by organizational populations. The emergence of differentiation may spur new imitation, first increasing diversity and then reducing it. The reversibility of the cycle may then explain oscillations in diversity as stemming from moving targets. Needless to say, further research is needed to prove these speculations.

Particularly interesting would also be to analyze settings that allow one to study the interactions between population-level diversity dependence and resource partitioning. In the present study, we were able to show that diversity dependence operates after controlling for traditional resource partitioning variables. It is, however, fair to say that in the present setting scale-based resource partitioning did not (yet) take place. An important question remains, therefore, what would happen if scale-based partitioning is forcefully present. In other words, how do the two processes interact? The theory we proposed is a theory on the distribution of firms over niches, net of size differences between firms. Resource partitioning is not only a theory on the former, but also a theory on the distribution of organizational mass (size) over niches. One might speculate that scale economies both amplify processes of convergence while at the same time increase the competitive effect of similarity. It is also likely that scale economies have an important impact on the trajectory of population-level diversity. Scale economies probably accelerate the segregation and bifurcation processes in populations, leading to symbiotic sub-forms. An important question is to find out when the processes of commensalism are strong enough to reverse the segregating force of scale economies. We think that the automobile or the beer brewing industries, where diversity resurgence have been observed and resource partitioning is forcefully present (Carroll and Hannan, 2000), are good candidates to study the interaction of both theories.

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7Figure 1: A system dynamics representation of diversity-dependence theory

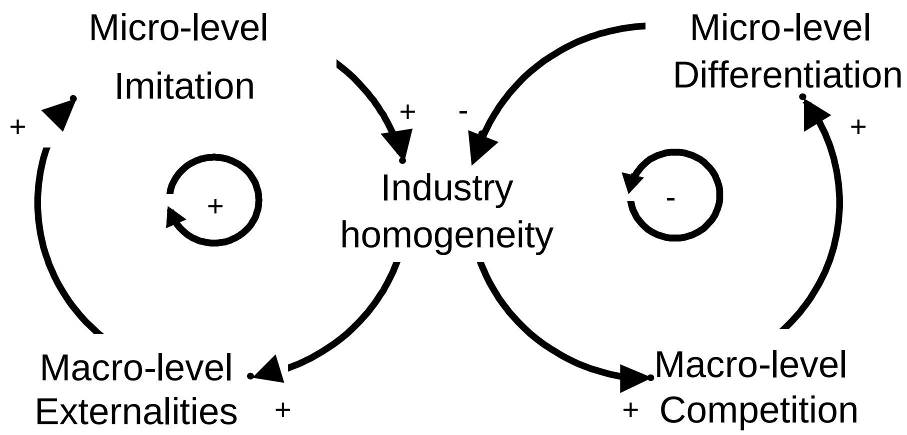

Figure 2: Density of UK motorcycle producers from 1895 to 1993

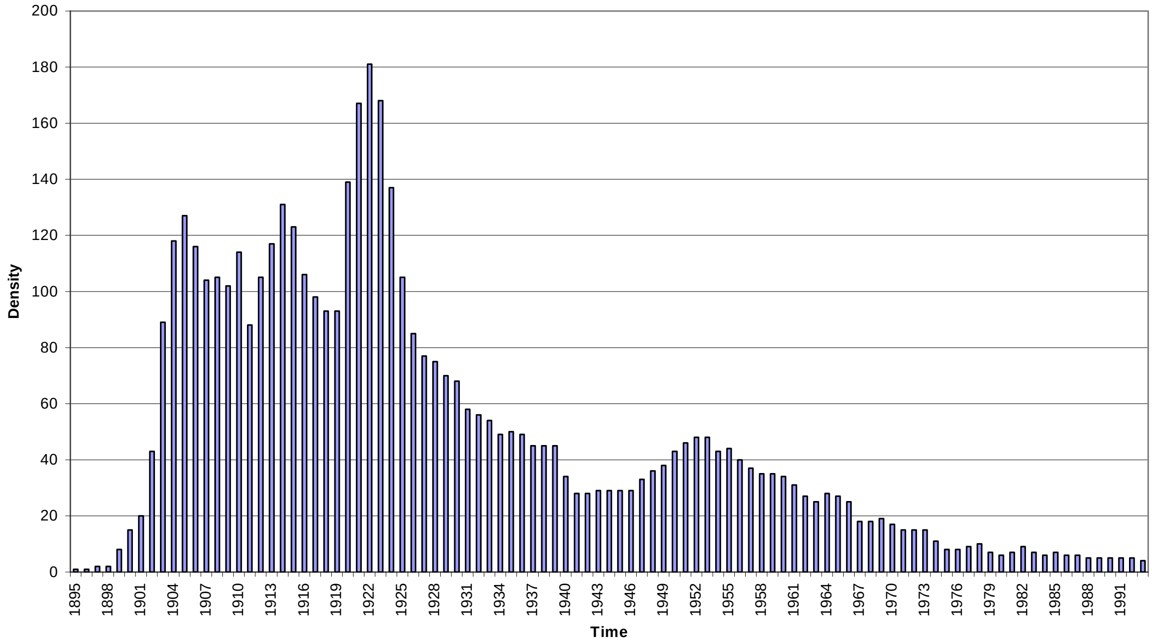

Figure 3: Composition of cc-categories in the UK motorcycle industry, 1895-1993

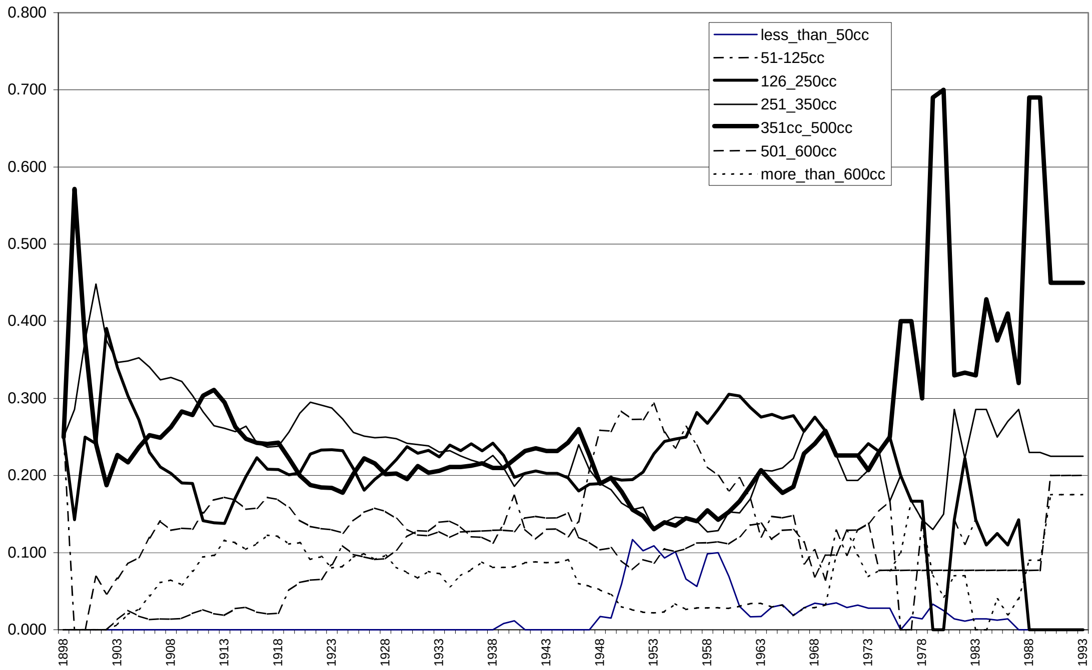

Figure 4: Simpson Index of Population-Level Homogeneity in the UK motorcycle industry from 1895 to 1993

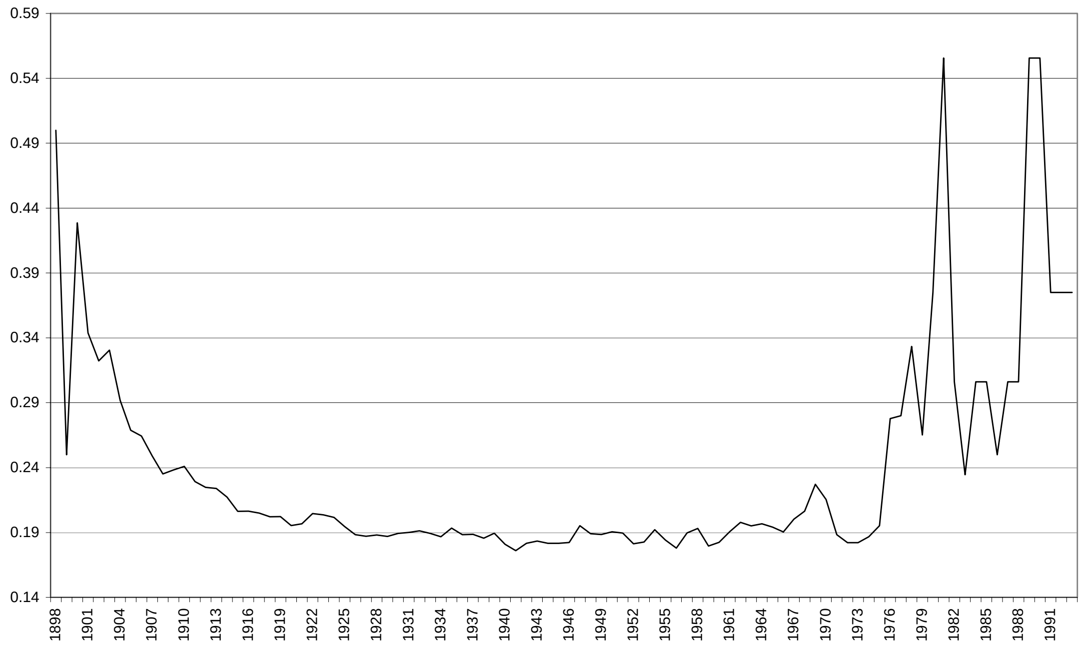

Figure 5: Interaction effect of Niche Overlap and Population-Level Homogeneity

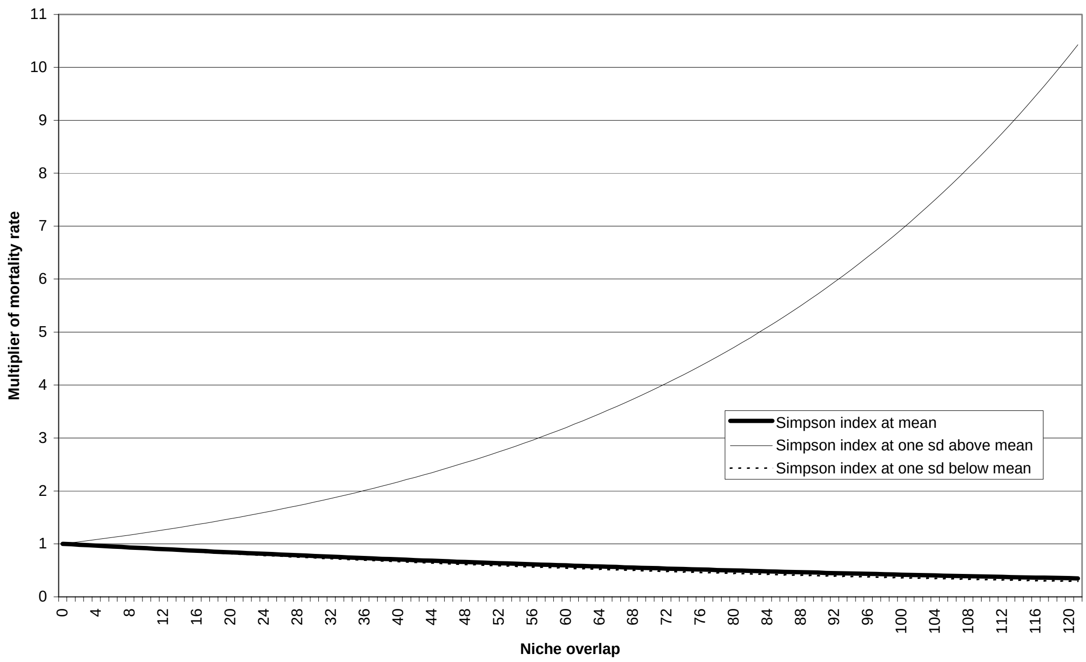

Table 1: Hypothetical working examples of Simpson index

cc-categories$_i$	**Proportion of firms producing in cc-category$_i$**			
	Example 1	**Example 2**	**Example 3**	**Example 4**
< 50cc				
51 - 125cc	.25	.20		
126 - 250cc	.25	.20		.05
251 - 350cc	.25	.20		.05
351 - 500cc	.25	.20	.50	.45
501 - 600cc		.20	.50	.45
> 600cc				
Simpson index	.25	.20	.50	.41

Table 2: Descriptive statistics for the exit analysis

		Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	WWI	0.09	0.29	1.00															
2	WWII	0.04	0.20	-0.07	1.00														
3	Post-1958	0.10	0.30	-0.10	-0.07	1.00													
4	Age	13.29	14.98	-0.11	0.23	0.32	1.00												
5	With Peak	0.84	0.37	-0.04	0.02	0.06	0.18	1.00											
6	District	0.53	0.51	0.05	-0.01	-0.07	0.16	0.02	1.00										
7	GDP per Person	0.23	0.73	-0.06	-0.02	0.53	0.10	0.02	-0.12	1.00									
8	Size (log)	0.43	0.55	0.02	0.10	-0.05	0.31	0.12	0.08	-0.09	1.00								
9	Average Scale	1.89	4.31	-0.12	-0.05	0.63	0.22	0.02	-0.11	0.62	-0.07	1.00							
10	Niche Overlap	44.42	27.19	0.11	-0.23	-0.44	-0.44	0.11	0.07	-0.30	-0.06	-0.44	1.00						
11	Total Motorcycle Sales (log)	3.88	1.00	-0.12	0.03	0.77	0.38	0.04	-0.11	0.65	-0.04	0.64	-0.58	1.00					
12	DeIpso	0.10	0.30	-0.01	0.05	0.04	0.12	0.02	0.01	0.04	0.14	0.03	-0.11	0.08	1.00				
13	DeAlio	0.48	0.50	0.03	0.02	-0.05	0.18	0.03	0.28	-0.05	0.04	-0.03	-0.07	-0.06	-0.31	1.00			
14	Density	90.43	46.58	0.11	-0.26	-0.49	-0.48	-0.05	0.03	-0.33	-0.10	-0.49	0.51	-0.64	-0.11	-0.07	1.00		
15	Niche Width	210.10	211.38	0.04	0.10	-0.03	0.33	0.43	0.07	-0.01	0.20	-0.01	-0.09	-0.02	0.07	0.10	-0.06	1.00	
16	Population-Level Homogeneity	0.21	0.04	-0.07	-0.16	0.08	-0.29	-0.06	-0.08	0.38	-0.16	0.24	-0.03	0.10	-0.09	-0.03	-0.02	-0.17	1.00

Table 3: Descriptive statistics for the entry analysis

		Mean.	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12
1	WWI	0.051	0.221	1.00											
2	WWII	0.007	0.088	-0.02	1.00										
3	Post-1958	0.050	0.218	-0.05	-0.02	1.00									
4	GDP per Person	0.140	0.372	-0.04	0.00	0.65	1.00								
5	District	0.394	0.489	0.06	-0.04	-0.04	-0.03	1.00							
6	Average Scale	3.61	1.29	-0.06	0.05	0.57	0.59	-0.02	1.00						
7	Total Motorcycle Sales (log)	1.16	3.61	0.01	0.01	0.33	0.32	-0.05	0.31	1.00					
8	DeIpso	0.053	0.224	0.01	0.06	-0.02	0.06	0.02	0.05	0.03	1.00				
9	DeAlio	0.289	0.453	-0.02	-0.06	-0.02	0.00	0.20	0.03	-0.09	-0.15	1.00			
10	Niche Width	87.48	113.12	-0.01	-0.05	-0.02	-0.03	0.04	-0.03	0.01	0.03	0.05	1.00		
11	Density	107.9	46.81	0.03	-0.13	-0.42	-0.31	-0.01	-0.56	0.22	-0.06	-0.18	0.02	1.00	
12	Population-Level Homogeneity	0.22	0.046	-0.10	-0.08	-0.10	-0.12	0.05	-0.04	-0.54	-0.04	0.11	-0.02	-0.38	1.00

Table 4: Maximum likelihood estimates of piecewise exponential model for exit rates of UK motorcycle producers in 1895-1993

Variables	Model 1	Std. Err.	Model 2	Model 2	Model 3	Std. Err.	Model 4	Std. Err.
WWI	-.170	.159	-.174	.159	-.284	.162 *	-.257	.161
WWII	1.06	.348 **	1.05	.351 **	.980	.364 **	1.19	.353 **
Post-1958	-.352	.310	-.296	.303	-.088	.272	-.225	.296
Age 0-1	-7.29	2.02 **	-7.36	2.04 **	-4.92	2.30 **	-9.96	3.16 **
Age 1-2	-7.53	2.02 **	-7.51	2.04 **	-5.12	2.30 **	-10.14	3.16 **
Age 2-3	-7.47	2.02 **	-7.54	2.05 **	-5.07	2.30 **	-10.06	3.17 **
Age 3-6	-7.73	2.02 **	-7.81	2.05 **	-5.37	2.31 **	-10.36	3.17 **
Age 6-10	-7.58	2.02 **	-7.65	2.05 **	-5.24	2.31 **	-10.19	3.16 **
Age 10-∞	-7.93	2.02 **	-7.99	2.05 **	-5.645	2.30 **	-10.65	3.17 **
50cc	.176	.203	.247	.189	.035	.201	.111	.208
125cc	.489	.121 **	.522	.119 **	.335	.123 **	.319	.123 **
250cc	.046	.096	.064	.095	.102	.094	.058	.096
350cc	-.071	.125	-.044	.124	.003	.123	-.012	.125
500cc	-.022	.109	.004	.108	.038	.108	.058	.107
600cc	.179	.163	.193	.161	.167	.159	.136	.163
With Peak	-.402	.115 **	-.411	.114 **	-.376	.115 **	-.374	.115 **
District	-.330	.078 **	-.328	.078 **	-.351	.078 **	-.369	.079 **
GDP per Person	-.748	.312 **	-.701	.304 **	-.504	.298 **	-.640	.324 *
Size (log)	-.884	.110 **	-.895	.110 **	-.945	.112 **	-.949	.111 **
Average Scale	.051	.027 *	.067	.028 **	.088	.030 **	.077	.034 **
Total Motorcycle Sales (log)	.527	.154 **	.515	.155 **	.400	.170 **	.552	.172 **
DeIpso	-.647	.150 **	-.638	.148 **	-.684	.145 **	-.686	.144 **
DeAlio	-.632	.098 **	-.629	.097 **	-.633	.098 **	-.626	.098 **
Niche Overlap	.016	.003 **	.016	.003 **	.012	.003 **	.285	.073 **
Density	-.037	.014 **	-.038	.014 **	-.043	.016 **	-.049	.015 **
Density^2/100	.03	.01 **	.03	.01 **	.04	.01 **	.05	.01 **
Niche Width/100	-.08	.05 *	-.06	.05	-.08	.05 *	-.07	.05
(Niche Width/100)*Average Scale			-.016	.009 *	-.016	.009 *	-.016	.01 *
Population-Level Homogeneity (*SI*)					-15.12	4.72 **	12.11	19.17
Population-Level Homogeneity^2 (SI^2)					25.66	11.74 **	-44.99	55.41
Niche Overlap**SI*							-3.118	.861 **
Niche Overlap*SI^2							8.311	2.467 **
Log-likelihood	-890.87		-888.93		-879.27		-872.98	
Number of observations	4685		4685		4685		4685	
Number of events	598		598		598		598	

* p < .05; and ** p < .025. One-tailed t-tests.

Table 5: GEE estimates of new entrants' similarity in the UK motorcycle industry in 1895-1993

Variables	Model 1	Std. Err.		Model 2	Std. Err.		Model 3	Std. Err.	
WWI	.665	.456		-.051	.131		.005	.114	
WWII	-.778	.497		-.020	.253		.001	.262	
Post-1958	-1.40	.312	**	-.136	.161		-.248	.157	
GDP per Person	-.259	.235		-.253	.137	*	-.283	.135	*
District	.095	.041	*	.060	.044		.069	.044	
Average Scale	-.050	.027	*	-.019	.016		-.022	.016	
Total Motorcycle Sales (log)	.338	.095	**	.117	.032	**	.141	.069	**
DeIpso	-.015	.092		-.012	.096		.001	.096	
DeAlio	-.126	.046	**	-.090	.049	*	-.094	.049	*
Niche Width/100	.03	.01	**	.03	.01	**	.04	.02	**
Density				.032	.003	**	.031	.003	**
$Density^2/100$				-.013	.001	**	-.010	.001	**
Population-Level Homogeneity							11.06	4.82	**
Population-Level $Homogeneity^2$							-19.45	6.48	**
Constant	2.11	.392	**	.881	.161	**	-.435	.993	
Wald chi-square	216.39			1022.05			1273.68		
Number of observations	644			644			644		

* $p < .05$; and ** $p < .025$. One-tailed t-tests.

Table 6: Incumbents' change: consequences, antecedents and aggregate impact

Variables	DV: niche center change		DV: exit		DV: *SI* absolute change	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
WWI	-.881	.200 **	-.242	.161	.026	.014 **
WWII	-.430	.371	1.20	.352 **	-.054	.019 **
Post-1958	.773	.348 **	-.233	.297	-.059	.024 **
Age 0-1			-9.96	3.14 **		
Age 1-2			-10.18	3.13 **		
Age 2-3			-10.10	3.14 **		
Age 3-6			-10.37	3.14 **		
Age 6-10			-10.22	3.13 **		
Age 10-∞			-10.67	3.14 **		
Age	.006	.013				
Age2/100	-.01	.02				
50cc	.261	.314	.107	.205		
125cc	.175	.136	.317	.121 **		
250cc	.274	.108 **	.046	.095		
350cc	.141	.131	-.019	.123		
500cc	.107	.131	.054	.106		
600cc	.262	.148 *	.126	.161		
With Peak	.708	.215 **	-.381	.113 **		
District	.141	.092	-.371	.079 **		
GDP per Person	.391	.146 **	-.647	.327 *	.003	.004
Size (log)	-.031	.091	-.950	.110 **		
Average Scale	.011	.034	.076	.034 **		
Total Motorcycle Sales (log)	-.211	.163	.557	.172 **		
DeIpso	.075	.135	-.689	.144 **		
DeAlio	.049	.100	-.626	.097 **		
Niche Overlap	.049	.065	.283	.072 **		
Density	-.017	.010 *	-.049	.015 **	-.292	.011 **
$Density^2/100$	.016	.009 *	.04	.01 **	.001	.005 **
Niche Width/100	.011	.039	-.07	.05		
(Niche width/100)*Average Scale	-.010	.009	-.016	.01 *		
Population Homogeneity (*SI*)	2.73	14.04	12.18	18.75		
Population-Level $Homogeneity^2$ (SI^2)	-27.55	36.44	-44.62	54.10		
Niche Overlap**SI*	-.701	.756	-3.08	.854 **		
Niche Overlap * SI^2	2.24	2.13	8.23	2.44 **		
Niche Center Change			.197	.105 *		
Births/100					.13	.06 **
Deaths/100					.08	.03 **
Total Niche Center Change/100					.04	.08
Constant	4.09	2.35 *			.253	.075 **
Log-likelihood			-871.75			
Wald chi-squared	132.43				38.70	
Number of observations	4685		4685		98	

* p < .05; and ** p <. 025. One-tailed t-tests.

NOTES

[1] Note that this definition follows standard practice in biology, where biological diversity is generally defined as "the variety and abundance of species in a defined unit of study" (Magurran, 2003: 8). As we study variation among organizations across positions in product market niches, we will focus on system heterogeneity [or horizontal differentiation in Industrial Organization (IO)], and not on inequality (or vertical differentiation in IO) – see Blau (1977).

[2] Note that Hawley (1950: 209) distinguishes two different types of mutualism: commensalism and symbiosis. Commensalism (which literally means eating from the same table) refers to positive interdependence among "units of like forms", based on supplementary similarity. Symbiosis pertains to positive interdependence of "unlike forms", based on complementary differences (see also Barnett and Carroll, 1987).

[3] Note that the models differ in the way in which the equilibrium is reached. Hawley argues that losing competitors are transformed; the resource partitioning model predicts that those units die and that differentiation comes from new entries. We return to this issue later in the paper.

[4] Units involved in multiple other settings face a similar trade-off. In the realm of human ecology, Hawley (1986: 89) comments that, "[b]roadly speaking, a temporal-spatial pattern represents a resolution of opposing tendencies. On the one hand, interdependence with its demand for interunit accessibility exercises a centripetal tendency; units of organization are drawn toward a concentration of locations. Human settlement is characteristically nucleated therefore. On the other hand, competition for location, operating in conjunction with diverse location requirements, develops a centrifugal tendency. Units are thrust outward from a point of maximum accessibility in keeping with their inabilities to use space intensively." Similar trade-off processes

has also been described in bio-ecology, where resources attract specific phenotypes leading to phylogenetic similarity whilst, at the same time, this similarity leads to repulsion of closely related phenotypes (Webb, Ackerly, McPeek, and Donoghue, 2002).

[5] We decided to start from homogeneity (instead of its opposite: diversity / heterogeneity) in Figure 1, and also below when we develop formal hypotheses and measures, only because this facilitates explaining the logic of the argument. In other parts of the text, we use the terms interchangeably for the sake of variation.

[6] Note that our reasoning is similar to "frequency-based imitation" in neo-institutional theory, where it is assumed that organizations use the proportion of other organizations applying a specific routine as a basis of adopting the routine itself (Haunschild and Miner, 1997). In our case, entrepreneurs use frequencies of firms in different niches as a signal to decide where to enter. For a description of similar processes in the realm of the development of regional industrial clusters, see Romanelli and Khessina (2005).

[7] In the theoretical case of 'complete' diversity – i.e., no explicit signal stemming from a dominant position – the emergence of such a dominant organizational position may occur through a random process. Note, however, that our theory predicts that populations of organizations oscillate between homogeneity and diversity. Given that the search for mutualism and externalities continuously drives organizations towards homogeneity, it is unlikely that populations ever reach 'complete' diversity.

[8] Given the uncertainty associated with establishing new ventures, this by no means implies that the 'outcomes' of these entrepreneurial decision heuristics are rational (in the sense of optimal). For instance, entrepreneurs tend to cluster in geographical space even in the absence of agglomeration economies (Sorenson, 2003).

[9] Interestingly enough, our coding of this specific category is identical to that of the Japanese Association of Motorcycle and Automobile Producers (see http://www.jama.org/statistics/motorcycle/production/mc_prod_year.htm).

[10] Note that Dobrev et al. (2001, 2002) could only identify the cc-range in which automobile firms were engaged, whereas we have information on all the models that compose an organization's portfolio on a year-by-year basis. This allows us to map the precise position of firms in technological resource space (for a comparable approach in the disk drive industry, see Barnett and McKendrick, 2004).

[11] Although we could have treated the 'unknown cases' as events by themselves, governed by its own transition rate, we followed the advice of Dobrev et al. (2001) not to do so. The problem is that missing information on exits mostly occurs for organizations with short longevity. "Because availability of information on the kind of exit depends (strongly) on tenure in the industry … this analytical strategy would confound the specification of the state space (the origin and destination states) and tenure" (Dobrev et al., 2001: 1311).

[12] We realize that an empirical test of Hypothesis 3 designed in this way is aimed at investigating only the successful attempts at founding, excluding unsuccessful ones and presuming a strong relationship between them – for a very interesting discussion on this issue, see Carroll and Khessina (2006). While we acknowledge the possibility of a loose coupling between the two events, our choice remains consistent with ecological studies that have built on this assumption (see Carroll and Khessina, 2006). Moreover, our approach is supported by the extensive evidence collected within the niche overlap (Baum and Singh, 1994a) and resource partitioning tradition (Carroll, 1985). Both theories, as well as density dependence (Hannan, 1986), assume that entrepreneurial decision-making is inspired by intended rationality and predict that

under crowding (either in product space or due to scale-based competition) less crowded positions in product space will experience more foundings.

[13] Although presenting slightly different values, the pattern of the *SI* computed for the entry analysis is remarkably similar to that of Figure 3.

[14] One of the reviewers pointed out that Total Motorcycle Sales, defined as the number of new registrations in the industry, confounds information on national production with (Japanese) imports that increased dramatically from the 1960s onwards. As this variable is the nominator of Average Scale, (s)he expressed doubt that this concentration proxy allows one to control for partitioning dynamics. Empirical evidence, however, suggests that imports did not reach a significant magnitude until the late 1950s – i.e., they accounted for less than one per cent of the number of total motorcycles produced between 1929 and 1937 (Koerner, 1995: 57), as well as in 1950, but they moved to 20 per cent in 1955 and up to 40 per cent in 1960, the year in which the industry's balance of trade became negative (Smith, 1981: 12). Based on this evidence, we recognize that our Average Scale measure could imprecisely measure concentration processes from the 1960s onwards. We, therefore, include a dummy indicating the Japanese era in all analyses (see below). To be on the safe side, we also redid both entry and exit analyses by selecting a further point of discontinuity, excluding the years after 1958 – the year in which Japanese competitors emerged as legitimized players thanks to the first success in the TT trophy. All findings related to the tests of our hypotheses in this sub-period (available upon request) are highly consistent with the ones reported here.

[15] Organizations with high market domain (or niche) overlap frequently encounter each other in multiple product markets. Multimarket theory argues that multiple encounters increase the possibility of multimarket retaliation, tempering rivalry. This

reduction of aggressiveness is known in the literature as mutual forbearance (Baum and Korn, 1996; van Witteloostuijn and van Wegberg, 1992) and implies that "firms that are close competitors may not be intense rivals" (Baum and Korn, 1996: 257). Therefore, we re-did all our analyses after adding the multi-contact variable used by, e.g., Baum and Korn (1996) – i.e., the annual count of the number of organizations that do overlap with the focal one in at least two niches. This variable turned out to be non-significant, without affecting the results reported here (available upon request). This finding suggests that collusion and mutual forbearance are not important in the present setting.

[16] It is empirically possible that a spurious non-linear relationship emerges between *SI* and new entrant's similarity even if entrepreneurs randomly enter niches in the market. This is due to the fact that the *SI* is bounded between 1/7 and 1. So, at a maximum *SI* the probability increases that new entrants will be dissimilar just by chance, and vice versa. We think this is an unlikely alternative explanation as our *SI* never reaches its boundaries in the period under study. However, to rule out this random entry baseline more formally, it suffices to show that the entry process does not follow a random walk (we thank Olav Sorenson for this suggestion). We find that there is a significant positive relationship between the number of foundings at time t and the number of foundings at $t-1$ in each niche, implying that entry is not random. This excludes the alternative random baseline explanation.

[17] The results were obtained by estimating a complementary log-log model through the GEE method and defining an exchangeable working correlation matrix.

[18] We corrected for autocorrelation in the time-series by adopting an ARIMA method with three lags.