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VARIETIES OF COMPETITIVE PARITY

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Strategy research explains why some firms outperform others, typically using profit rates, shareholder returns, and other continuous dependent variables. This paper investigates winning as the dependent variable, as measured by distributions of annual industry leadership in profits and returns to investors. This shift in dependent variable introduces alternative null models of competitive parity, including skew distributions derived from the natural sciences, and empirical distributions from nonbusiness domains such as chess, politics, sports, and beauty pageants. An empirical study of 20-year leadership in U.S. industries shows that performance distributions in business follow statistical power laws resembling those in natural phenomena, and closely resemble distributions found in sports, politics, and other nonbusiness domains. The results support a presumption of persistent performance advantages in business, but show that business outcomes are indistinguishable from outcomes in the wider scientific and competitive landscape, and are amenable to explanation using relatively simple heuristics. The paper shows how the choice of null model shapes firm performance explanations, and explores the consequences of a more inclusive approach to null models in strategy research. Copyright © 2002 John Wiley & Sons, Ltd.

STRATEGY AND FIRM PERFORMANCE

Amid the diversity of strategic management research runs a persistent concern with explaining variations in firm performance (Rumelt, Schendel, and Teece, 1994; Grant, 1998; King and Zeithaml, 2001). The central, brute empirical fact in strategy is that some firms outperform others. Strategy theories explain this fact, and empirical studies investigate its underlying causes, for example identifying firm-specific performance correlates (Hansen and Wernerfelt, 1989; Powell, 1995), examining the persistence of abnormal returns (Jacobsen, 1988; Waring, 1996; Goddard and Wilson, 1999), and decomposing variance into industry, corporate, and business-specific effects (Rumelt, 1991; McGahan and Porter, 1997; Brush, Bromiley, and Hendrickx, 1999).

Mainstream empirical research often uses continuous accounting profit rates as the dependent variable. There are important exceptions (e.g., shareholder returns, organizational mortality rates), but the current range of alternatives may be cause for concern. In particular, evidence suggests that performance explanations are latent in the dependent variables they explain (Meyer and Gupta, 1994; March and Sutton, 1997; Wensley, 1997): 3- to 5-year profits correspond to executives' tenures and planning horizons, and are conducive to firm-specific, managerial explanations (Rouse and Daellenbach, 1999; Spanos and Lioukas, 2001); longer-term profit rates randomize short-term fluctuations, bringing market structures into account (Mueller, 1986; McGahan, 1999); long-term mortality rates

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yield ecological and institutional theories (Hannan and Freeman, 1989; Baum, 1996); cross-national comparisons yield cultural, demographic, and geographic explanations (Porter, 1990); shareholder returns produce stochastic and event-based explanations (Jarrell, Brickley, and Netter, 1988; Reuer, 2001); and research on long-term change yields theories of cycles, path dependency, and punctuated equilibrium (Gersick, 1991; Romanelli and Tushman, 1994; Morel and Ramanujam, 1999). As March and Sutton point out:

> It is often unclear what variable should be treated as causally dependent. The choice is made by the researcher ... This judgment may be valid, but it cannot be confirmed by the analysis, which can only assess the likely strength of the relationships on the assumption that the causal structure is correctly specified. (March and Sutton, 1977: 342)

Strategy researchers could arguably produce more uniform results, and improved theoretical integration, by narrowing the field of dependent variables (Meyer and Gupta, 1994). But paradigm consensus exacts a heavy price—if firm performance is inherently complex and multivariate, then performance research needs variety in the dependent variable. In strategy research especially, it seems unwise to constrain or preordain the wide field of discovery about firm performance.

This paper investigates *winning* as the dependent variable, construing performance as the distribution of long-term frequencies of industry leadership, as measured by rank orderings of total profit, profit rates, and returns to shareholders. Using 20-year *Fortune* data, the paper investigates the statistical properties of frequency distributions of wins, and compares these with null distributions produced analytically, empirically, and by simulation.

The choice of long-term frequency distributions shifts the conceptual emphasis from firm-specific performance to distribution-wide competitive dominance and, as a consequence, to null models of competitive parity. Because interpretations of competitive dominance are colored heavily by expectations, the paper develops four alternative models of competitive parity: equal performance ('perfect parity'), randomly varying performance ('stochastic parity'), skew distributions ('Pareto parity'), and performance in nonbusiness domains ('natural parity').

Whereas strategy research traditionally emphasizes stochastic parity (and to some extent, perfect parity), the current study develops the case for null models derived from other social, biological, and physical sciences (Pareto parity), and from nonbusiness competitive domains like football and beauty pageants (natural parity). The empirical data show that firm performance distributions resemble those in other sciences and in nonbusiness domains, and the paper explores how these resemblances can illuminate new empirical and theoretical pathways for strategy research. More generally, the findings demonstrate the power of the dependent variable to shape performance explanations, and they argue strongly for greater variety in our null models of competitive parity.

The following section briefly positions the paper in relation to strategy research using profit rates as the dependent variable. Subsequent sections develop the four null models, present the data and results, and discuss their implications for strategy research.

CONTINUOUS PROFIT RATES AS DEPENDENT VARIABLE

Continuous profit rates are the most commonly used dependent variable in strategy research, and they illustrate the coupling of theory and dependent variable in strategy. Studies of short-term profit rates tend to emphasize firm-specific advantages: the PIMS research examined short-term ROI in producing its findings on market share and product quality (Buzzell, Gale, and Sultan, 1975); in comparing the relative effects of organizational and economic factors, Hansen and Wernerfelt (1989) used 5-year inflation-adjusted profit rates (ROA); in studying differences within strategic groups, Lawless, Bergh, and Wilsted (1989) used industry-adjusted short-term profit rates (ROS, ROE, ROA); in studying the firm-specific performance effects of TQM initiatives, Powell (1995) used executives' responses on Likert scales of 3-year profit performance, then validated these against objective profit measures (ROS, ROA); and, in studying the impacts of causally ambiguous competencies, King and Zeithaml (2001) used unadjusted short-term profit rates (ROA).

The persistent profitability literature emphasizes longer-term abnormal accounting profits, investigating persistence across various industry sectors and national contexts, e.g., the persistence of 23-year profit rates in U.S. manufacturing (Mueller, 1986); 21-year profit rates in German manufacturing (Geroski and Jacquemin, 1988); 20-year profit rates in U.S. manufacturing and services (Jacobsen, 1988); 19-year profit rates in Japanese manufacturing (Odagiri and Yamawaki, 1990); 20-year profit rates in U.K. manufacturing and services (Goddard and Wilson, 1996); 17-year profit rates in U.S. pharmaceutical firms (Roberts, 1999); and 20-year profit rates in Australian manufacturing (McDonald, 1999). Unlike shorter-term research, the findings emphasize structural and market forces, and are broadly consistent with Jacobsen's (1988:415) threefold conclusion: (1) a variety of factors influence the persistence of profit rates; (2) market factors generally drive profits back to competitive rates; and (3) notwithstanding (2), business-specific factors can isolate a firm from competitive forces and produce long-term abnormal profits.

In variance decomposition research, profit rates have been used to estimate industry, corporate, and business effects over a variety of time periods. Schmalansee (1985) used 1-year profit rates (ROA) as the dependent variable across 1800 business units in the 1975 FTC Line of Business (LB) data; Rumelt (1991) used 4-year profit rates (ROA) for two samples in the 1974–77 FTC LB data; and McGahan (1999) extended Wernerfelt and Montgomery's (1988) usage of Tobin's q, a continuous measure incorporating investor expectations about future accounting profit rates, estimating 14-year industry, corporate, and business effects for 4900 U.S. corporations. The findings depend largely on time horizons and industry contexts, but generally support the conclusion that industry and business effects far exceed corporate effects, with business effects somewhat greater than industry effects (Bowman and Helfat, 2001).

Accounting profit rates need little justification as a dependent variable—they are clearly relevant to strategy research, and the uniformity of measurement has facilitated the field's development toward firm-specific, resource-based accounts of superior performance. But the dependence of theory on the choice of performance measure is not widely acknowledged. In particular, continuous profit rates carry both a latent, stochastic null model of profit behavior (random variations from 'normal' profit rates), and an explanation for departures from that null (variations in continuous independent variables). Ultimately, econometric studies emphasize effect sizes, with differences stemming largely from method and sampling variance. Thus, short-term profit rates presage firm-specific effects (Rumelt, 1991; Hansen and Wernerfelt, 1989; Powell, 1992, 1995); longer-term profit rates bring exogenous industry factors into account (Mueller, 1986; Jacobsen, 1988; McGahan, 1999); and single-industry profit rates yield firm-specific attributions, e.g., attributing persistence in pharmaceuticals to firm-specific innovation (Henderson and Cockburn, 1994; Roberts, 1999).

In sum, econometric studies of profit rates have contributed much to our understanding of firm performance, but their findings are constrained by the choice of dependent variable—the studies identify key independent variables and measure their effect sizes, but they cannot do more. If performance is complex, and if explanations are latent in the dependent variable, then strategy research requires multiple dependent variables and a wider assortment of null models. As evidenced in less traditional dependent variables, such as organizational mortality rates, alternative performance conceptions are possible, and can contribute valuable new methods and insights in strategy. This paper conceptualizes firm performance as 'winning,' and shows how this change of variable illuminates alternative empirical methods, null models and theoretical connections.

WINNING AS DEPENDENT VARIABLE

To conceptualize winning as the dependent variable, it is useful to consider a stylized industry in which n firms compete over t years, without entry or exit. Assume that each firm attempts to lead this industry in some performance measure, which we track year by year, ranking each firm 1 through n for each year 1 through t. In particular, we are interested in how many times each firm ranks first in performance over the t years.

The zero entry and exit assumptions are unrealistic and rarely satisfied in industry, but can be found in other competitive domains. In professional baseball, for example, the same 12 teams competed for the National League championship in the years 1969–88. We can imagine a scenario under which league championships were divided as equally as possible over this 20-year span. Under this scenario, each of the 12 teams would win the title at least once, and eight teams would win twice—thus, the distribution of wins would be 2,2,2,2,2,2,2,2,1,1,1,1.

In fact, the actual distribution of wins during that span was 5,4,3,3,2,2,1,0,0,0,0,0—the Dodgers won five times, the Reds won four, etc., and five teams never won. This outcome clearly diverges from the theoretical parity distribution (2,2,2,2,2, 2,2,2,1,1,1,1), and it would be useful to characterize this divergence statistically.

In characterizing this divergence, we refer to the null distribution as *perfect competitive parity*, and define it as *the condition that, over t years, each competitor finishes first t/n times, or if t/n is not an integer, rounded to its nearest equivalent*. Thus, for example, if 10 firms compete for 20 years, perfect parity is achieved if each firm wins twice. In the National League example, with 12 competitors over 20 years, perfect parity is achieved if each team wins 20/12 (or 1.67) times, in which case we make the rounding correction, with eight teams winning twice and four teams once.

Many statistical methods have been used to assess distributional disparities (see, for example, Atkinson, 1970, 1975), but by far the most widely used is the Gini coefficient (Xu, 2000). The Gini, developed originally to measure inequality in income distributions, ranges between 0 (perfect parity) and +1.00 (maximum disparity), and has been used to study disparities in a variety of applications (Chakravarty, 1988; Lee and Murnane, 1992). There is no clear and accepted standard by which to assess whether a Gini coefficient is 'large'—in the National League data, the Gini is 0.61, which in most contexts is relatively large.

The Appendix provides the formal method for calculating Gini coefficients for $t = 20$ periods, but the method is essentially that of the Lorenz curve, and can be shown graphically. For an industry with five firms competing for 20 years, perfect competitive parity produces a distribution such that each firm leads the industry (in, say, returns on sales) four times. This implies zero Gini, and all other distributions produce positive Ginis. In Figure 1, five firms are arrayed on the horizontal axis, from lowest performer to highest, and the columns show cumulative 'firsts' for each firm. Under perfect parity, 'firsts' are distributed 4,4,4,4,4, and cumulative firsts ascend stepwise 4,8,12,16,20. However, under alternative outcome 1,2,4,4,9, the cumulative distribution is 1,3,7,11,20. Graphically, the Gini coefficient for this outcome is the ratio of area A to area $[(A + B) - 20]$, in this case 18/40, or 0.45.

Perfect competitive parity, i.e., all firms winning the same number of times, constitutes a limiting case, in the sense that no other null could produce greater departures from empirical results, nor be as likely to invoke causal explanations. It can be shown, for example, that with five firms, the probability of the distribution 4,4,4,4,4 is 0.0032, even if all firms are identical (i.e., each firm wins with probability 1/5 in each period). Thus, an industry of five identical firms would produce a nonzero Gini 99.7% of the time, and where $n = 10$ firms, the proportion is 99.99%. Although we expect to observe perfect competitive parity in few empirical settings, the model has theoretical value as a benchmark for subsequent null models. Thus, we hypothesize as follows:

Hypothesis 1: Industry distributions of wins differ significantly from perfect competitive parity.

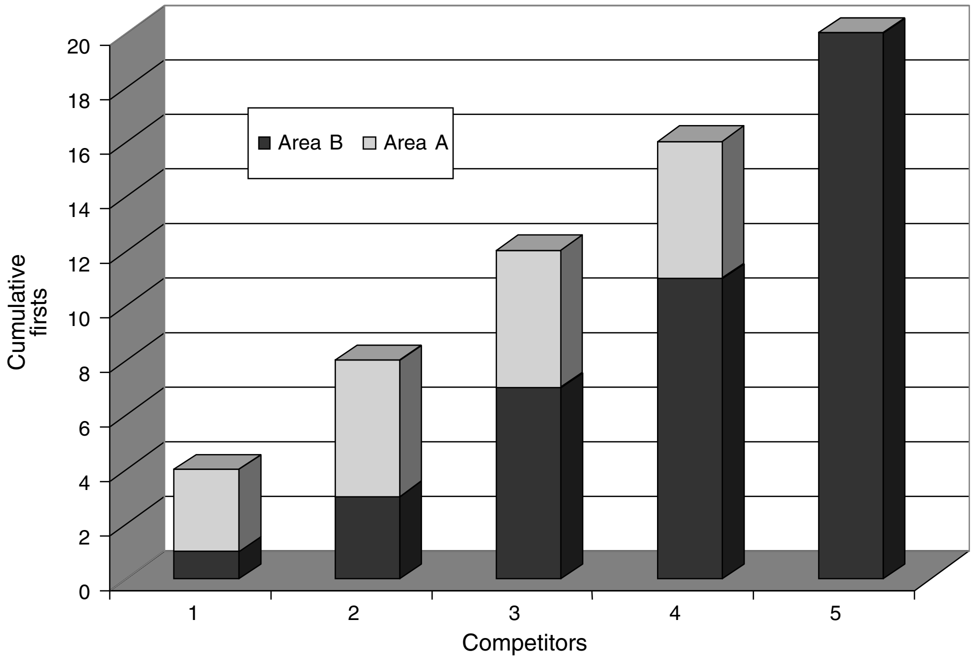
NULL MODELS AND COMPETITIVE PARITY

Stochastic parity

Strategy research traditionally tests null models of random performance variation, identifying firms with above-normal performance, or independent variables with statistically significant performance effects. In this study, the analogous null model compares actual Gini coefficients with expected Ginis under the assumption of random assignments of wins.

Because of formal idiosyncrasies in the computation of Gini coefficients, the analytical derivation of statistical moments for these coefficients is exceedingly complex. As an alternative, we derived the mean and standard deviation using the following simulation: five firms compete for 20 years, with each firm having probability 1/5 of winning in any year. Wins are distributed by a random number generator, and after 20 periods wins are counted and the Gini computed—the simulation is repeated to $N = 10{,}000$ trials, a mean and standard deviation are computed for the Gini coefficients, and the simulations repeated for industries of other sizes.

For example, in a hypothetical industry of $n = 5$ firms, the simulation produced 10,000



Competitor	Parity scenario firsts(x)	Parity scenario cum$x$	Alternative scenario firsts(x)	Alternative scenario cum$x$
1	4	4	1	1
2	4	8	2	3
3	4	12	4	7
4	4	16	4	11
5	4	20	9	20
$\sum$	20	60	20	42
	Area A + Area B = 60		Area B = 42	

$$\text{Gini} = \frac{\sum \text{cum}x\ (\text{parity}) - \sum \text{cum}x\ (\text{alternative})}{\sum \text{cum}x\ (\text{parity}) - 20} = \frac{60 - 42}{40} = 0.45$$

$$= \frac{\text{Area } A}{(\text{Area } A + \text{Area } B) - 20}\ \text{(see figure)}$$

Figure 1. The Gini coefficient

20-year Ginis with mean $= 0.28$ and standard deviation $= 0.08$; in an industry with $n = 15$ firms, the simulations produced mean $= 0.47$ and standard deviation $= 0.08$. If an industry of five firms produces an actual 20-year Gini of 0.40, we compute a z-score ($z = +1.50$) as a measure of the industry's departure from a random distribution of wins. This motivates the following hypothesis:

Hypothesis 2: Industry distributions of wins differ significantly from randomly generated distributions of wins.

This hypothesis, like Hypothesis 1, is not an assertion about a firm, but about a distribution of firm performance. Corroborating Hypothesis 2 for an industry would show that the distribution was skewed, but not that any firm was dominant, or that any firm had sustainable competitive advantages. On the other hand, a significant Gini can be interpreted as *prima facie* evidence of competitive dominance by one or a few firms (a necessary but not sufficient condition), a proposition easily testable by closer inspection of the distribution. For example, in National League baseball, the distribution 5,4,3,3,2,2,1,0,0,0,0,0 yielded a Gini coefficient of 0.61, and $z = 2.11$. Using a two-tailed test, a z-score of at least this magnitude would occur only 2.8 percent of the time if wins were distributed randomly. This suggests competitive dominance, although not an extreme case—on closer inspection we find that four teams won at least three times, and seven of twelve teams won at least once. This is not an instance of one-firm competitive dominance—an interpretation is that the Dodgers and Reds, combining for nine wins in 20 years, dominated National League competition between 1969 and 1988.

Pareto parity

Although stochastic null models are statistically convenient, they do not necessarily align with researchers' theories of competitive advantage, or with their true performance expectations. As Starbuck points out:

> Very often social scientists 'test' their theories against ritualistic null hypotheses (a) that the scientists can always reject by collecting sufficient data and (b) that the scientists would not believe no matter what data they collected and analyzed. As proofs of knowledge, such tests look ridiculous. (Starbuck, 1994: 215)

Adopting discrete win frequencies as a dependent variable suggests comparisons with the vast, and still growing, literature on rank–frequency relationships, which ranges across the physical, biological, linguistic, and social sciences. The seminal contribution, Vilfredo Pareto's income distribution theory, proposed that, when individual incomes are ranked, the rank–income relationship follows the form $I = cr^{-a}$, where I is income, r is rank, c is a constant roughly equal to the largest income, and a is a constant, usually in the neighborhood of 1.5. In other words, income is distributed such that Ir^{-a} is a constant, and that, with rank and income plotted on logarithmic axes, the relationship is linear, with slope $= -a$.

Harvard sociologist George Zipf proposed a similar model, with ranks (r) and frequencies (f) related by the form $f = cr^{-1}$(Zipf, 1949). This variant on Pareto's law sets $a = 1$ ($a = 0$ is perfect parity, all ranks having equal frequencies). Zipf tested this model across a variety of phenomena, with impressive results: the ranks and frequencies of words in James Joyce's *Ulysses*, plotted logarithmically, were linear with slope $= -1$; the 10th-ranked word appeared 2653 times, the 100th-ranked word 265 times, and the 1000th-ranked word 26 times. Moreover, Zipf found similarly robust, Pareto-like relations in studies of Homer's *The Iliad*, and in Chaucer, Shakespeare, Chinese literature, children's speech, Hebrew speech, American Indian speech, the *Chicago Tribune*, the *New York Times* and the *Encyclopedia Britannica*. Zipf also found power laws in schizophrenic speech; in rail and bus travel; in the species and genera of flowering plants and Chrysomelid beetles; in scholarly publications; in telephone messages; in the tonal intervals of Mozart concertos; in the ranks and sizes of cities, of service companies, of manufacturing companies, and of occupations.

Zipf's findings were replicated and extended by other researchers. Champernowne (1953) applied similar models to income distribution, Mandelbrot (1953) applied them to language distributions, and Steindl (1965) and others applied them to the size distributions of firms (Simon and Bonini, 1958; Quandt, 1966; Singh and Whittington, 1975; Sutton, 1998). Yuji Ijiri and Herb Simon published a series of monographs (Ijiri and Simon, 1977) applying Pareto, Zipf, and other skew distributions to scholarly publications, the genera of plants, the distributions of particles, and the sizes and growth of new firms. Krugman (1996) reported that the 1993 size distribution of U.S. cities followed Zipf's variant of Pareto's law, again with surprising accuracy: the log-linear slope was −1.003, and the 10th ranked city (Houston), with a population of 3.85 million people, was roughly 10 times larger than the 100th ranked city (Spokane), with 370,000. Krugman also reported that 'Zipf's law' ($a = 1$) applied to every U.S. census since 1890, and to other countries, as well as to natural and social phenomena including earthquakes, animal sizes, meteorites, business cycles, technology dissemination, and the sizes and frequencies of fragments from shattered urns.

Pareto relations gained renewed momentum in the physical and social sciences through recent developments in complexity theory, self-organized criticality, complexity, and coevolution (Gould, 1989; Kaufman, 1993; Gell-Mann, 1994; Levinthal, 1997; McKelvey, 1999). From a complexity theory perspective, firm performance arises in a complex system in which firms interact dynamically with each other and their environments to create highly variable, nondeterministic outcomes (Prigogine, 1980; Pascale, 1999; Anderson, 1999). Many phenomena in the physical sciences are not, in this sense, complex: planets follow predictable, nonvariable orbits, and crystals follow an orderly, well-understood process in which each atom occupies a defined space on a lattice. But other systems of scientific and social-scientific interest are complex, including biological competition, weather, landscape formation, tectonic plate movement, freeway driving, and shareholder behavior.

Because complex systems are nondeterministic, their specific behaviors and outcomes cannot be predicted, no matter how complex the theory or how great the computational power. But complexity theory asserts that these systems do 'self-organize' into broad behavioral and statistical patterns, the most conspicuous of which is the tendency to organize around Pareto-like power laws (Bak, 1996). In geological studies of turbidite sedimentation, the numbers of layers and their thickness are related by a power law with exponent $a = 1.4$; avalanche magnitude and frequency follow a power law with $a = 1.1$; earthquake magnitude and frequency follow $a = 1.4$; the numbers and lifetimes (until extinction) of genera follow $a = 2$; the magnitude and frequency of solar flares follow $a = 1.5$; and the magnitudes and frequencies of ricepile and sandpile avalanches follow different power laws, averaging roughly $a = 2$ (Chen and Bak, 1991; Grumbacher *et al.*, 1993; Carlson and Swindle, 1995; Frette, Christensen, and Malthe-Sorensson, 1996; Bak, 1996). In brief, complex physical phenomena of surprising diversity follow a power law with a between 1 and 2.

Power laws may reveal hidden order or 'self-organization' in complex phenomena, but there is little cross-disciplinary consensus on precisely why they work. Zipf's original explanation invoked the 'principle of least effort,' which he derived from the notions of 'forces of diversification' (D) and 'forces of unification' (U). In brief, all competition is subject to D and U, and the value a represents their equilibrium, i.e., the quotient D/U: when D exceeds U, then $a > 1.0$ and greater disparity is observed; when $U > D$, the opposite occurs. Zipf's system leaves D and U imprecise, but in organizational contexts they may be analogous to forces such as institutional heterogeneity and isomorphism (Meyer and Rowan, 1977), differentiation and integration (Lawrence and Lorsch, 1969), or corporate expansions and assimilations (Chandler, 1961). In strategy, a Zipf-like account might predict that forces for disparity (firm-specific resources, economic rents, monopoly power, individual wealth, etc.) and parity (diffusion of innovation, imitation, benchmarking, fads, bandwagons, etc.) would produce outcomes balanced on a power law with $a = 1$.

Zipf's theory produced impressive empirical predictions, but its underlying verbal account of 'least effort' and the interactions of D and U is not wholly convincing. In particular, it remains unclear how one would define D and U in context, or, more importantly, why D and U should produce an exponent in a power function (why not $\log(a)$, or e^a, or a^x?). Ultimately, Zipf's theory is suggestive, and his intuitions possibly correct, but 'least effort' does not yield a satisfactory explanation for a power law with $a = 1$.

Ijiri and Simon, working with similar results, produced a far more concise and convincing account. In brief, Ijiri and Simon showed, deductively and in simulation, that a power law necessarily results from any process in which competitors grow at rates independent of current endowments. This underlying process—known as 'Gibrat's assumption,' or the 'law of proportionate growth'—recognizes the empirical fact that, in many growth processes, the absolute growth of larger units exceeds that of smaller ones, but only in proportion to current mass. Krugman used this process to explain why size distributions of cities take the Pareto form with $a = 1$, and a variety of phenomena in the Ijiri–Simon studies (word distributions, firm growth, scholarly publications) were shown to follow proportionate growth processes.

Proportionate growth provides an essential theoretical linkage, missing in Zipf's account, between underlying physical, social, or economic processes and the forms of their resulting distributions. For example, we know that if firm sizes follow a proportionate growth process, then perfect parity cannot occur, and there is little use proposing it as a null model—the outcomes must form a skew distribution. Moreover, Ijiri and Simon showed that the exponent a can be interpreted as a function of entry conditions, an important linkage between the power law and competitive processes. We revisit this claim later in discussing our findings on firm performance.

The theory of self-organized criticality has produced an alternative account of power laws, arguing that extended stable periods create long-lasting, low-variance evolutionary stages, but that small variations accumulate to produce high-variance catastrophes (e.g., earthquakes, traffic jams, extinctions, volcanic eruptions, stock market crashes), much as in models of punctuated equilibrium (Bak, 1996). Whereas traditional equilibrium theories tend to discount catastrophic events as outliers, complexity theory treats catastrophes as system-defining milestones, and incorporates them statistically. When plotted logarithmically, the high-frequency evolutionary outcomes and low-frequency catastrophes organize themselves in linear form, i.e., in a power law.

In brief, power laws have yielded abundant empirical support and significant conceptual work, but have not yet produced an integrated theory. Taking previous empirical work as a guide, we speculate that a power law, with a between 1 and 2, comprises a reasonable expectation for firm performance. In the absence of further evidence, we adopt Pareto's formulation, as follows:

Hypothesis 3: Industry distributions of wins differ significantly from a power law with $a = 1.5$.

Natural parity

If conventional null models are incomplete, it is not for lack of insight or sophistication. Researchers' expectations about firm performance are, if anything, too well informed. They almost certainly reflect biases informed by shared academic training, experience, shared vocabulary, and social networks, and may embody logics arising from the very business distributions the researchers are trying to explain. In general, we are unlikely to produce surprising results by comparing business distributions only to each other, and we should welcome compatible models imported from other disciplines. Thus, we hypothesize the following null model:

Hypothesis 4: Industry distributions of wins differ significantly from those in other competitive domains.

Nonbusiness distributions are intrinsically interesting, but are also of conceptual value, both as alternatives to conventional strategy models and as counterpoints to theories of self-organization. It could be argued, for example, that a theory of self-organization does not follow from the existence of complex processes and power laws. In professional baseball, we know that many (though not all) owners and regulators value competitive parity, and implement rules and restrictions designed to promote 'socially-efficient team quality' (Canes, 1974), through draft restrictions, revenue-sharing, team salary caps and player free agency (Fort and Quirk, 1995). In the 20-year period 1945–64, the New York Yankees won the American League pennant 15 times—since 1964, when owners agreed to an unrestricted free-agent draft (over the objections of the Yankees and Dodgers), no team has approached such dominance. In professional sports generally, a large body of research has shown how powerful team owners and regulators proactively use social and political processes to establish objectives for performance distributions (usually to suppress competitive dominance), closely monitor the results, and apply remedies by manipulating game rules and structures (Demmert, 1973; Davis, 1974; Canes, 1974; Noll, 1974; Quirk and Fort, 1992; Fort and Quirk, 1995).

Under these institutional conditions, in which self-interested agents proactively engineer performance distributions to promote welfare preferences, it seems anomalous to call the outcomes 'self-organized.' Moreover, the regulation of business performance in advanced economies, though immeasurably more complex than in sports, involves analogous economic, institutional, and social processes (Schotter, 1986; Powell and DiMaggio, 1991; Chang, 1996). In principle, any domain's rules and structures determine its range of feasible performance distributions, and undesirable distributions can be reengineering through the 'visible hand' of contractual arrangements, property rights, and other institutional features (Chandler, 1977; Williamson, 1985; Coase, 1988). Moreover, these distributions necessarily reflect stakeholders' welfare preferences (i.e., implicit theories of procedural and distributional justice), as in baseball's strong revealed and expressed preference for competitive parity over the past 35 years.

We develop these ideas further in discussing the empirical findings, but for now we emphasize the following: (1) unlike earthquakes and other natural phenomena, performance distributions need not be exogenous nor self-organizing (or at least not predominantly so); (2) for any game, institutional rules and structures influence the range of feasible performance distributions; and (3) institutional arrangements are both descriptive and normative, i.e., they embody and reveal stakeholders' joint preferences about procedural and distributional justice.

DATA AND RESULTS

Empirical Gini coefficients

Gini coefficients seldom appear in strategy research, or in any research using continuous industry data, for two reasons. First, financial measures are unstable across industries (e.g., returns on assets are lower in capital-intensive industries, some firms and industries earn negative returns in some years), making Ginis computationally intractable; and second, industry entry and exit produce incomparable competitive sets over long periods, affecting estimates of n. The first problem is ameliorated by converting raw data to ranks, which also facilitates direct comparisons across competitive domains (though it entails a loss of data). But even with ranks the second problem persists—over time, more than n firms may have opportunities to finish 'first,' even if only n firms compete in any given year.

One way to address industry entry and exit is to confine the sample to the most stable subset of industry competitors, generally the largest competitors. For example, among all chemical producers in the United States, 42 appeared in the *Fortune* 500 in 1996, and over the period 1980–99 that number ranged from 38 to 43, with most entry and exit confined to the rankings 450–500. Similarly, among U.S. food producers, between 41 and 55 firms appeared in the *Fortune* 500 in the period 1980–99, with entry and exit confined mainly to rankings below 450.

Moreover, in the *Fortune* 500, 'entry' rarely means industry entry, and 'exit' rarely means industry exit—more commonly, entry means rising into the *Fortune* 500 from somewhere just below the list, and exit means falling below the 500 rank, or merger/acquisition, usually in the same industry. This is not always the case (e.g., *Fortune* 500 firms go bankrupt; tobacco firms acquire food companies), but the exceptions are infrequent. In the worst case, the disruptions are confined to misestimates of n (the number of firms), which would have the least disturbance in industries with the greatest entry and exit (i.e., largest n). Using Ginis, the best assessment of n arises with a fixed number of firms; but, in the face of messy facts, and with some adjustment, the *Fortune* 500 may provide a reasonable context for estimating Ginis.

Table 1 presents Gini coefficients for 21 U.S. manufacturing industries for the 20-year period 1980–99, taken from *Fortune* 500 data for those years. The data exclude: service industries (these were excluded from the lists prior to 1994); industries that changed definition during the period; industries that did not exist throughout the period; industries defined, in the researchers' assessment, as over-broad industry sectors (e.g., 'electronics,' 'motor vehicles and parts'); and conglomerates ill fitted to any industry (e.g., Berkshire Hathaway, Textron, General Electric). In some cases, industries were redefined within *Fortune*'s industry groups (e.g., 'motor vehicles' consists of GM, Ford, and Chrysler, separated from their suppliers).

In Table 1, the first column (n) is the average number of firms for each industry over the 20-year period, and the next five columns are the Ginis for five performance measures provided in the *Fortune* 500 data: total profit, return on sales (ROS), return on equity (ROE), 1-year yield to investors and 10-year yield to investors (*Fortune*'s measures of investor yield do not adjust for financial risk). The final column is a linear combination of the five performance measures, i.e., the mean of the five Ginis. All Gini coefficients were calculated as in the earlier examples, using the formula in the Appendix.

Hypothesis 1: Perfect parity

Hypothesis 1 is a 'straw null,' hypothesizing nonzero Gini coefficients. As expected, the results in Table 1 are quite inconsistent with a null of perfect competitive parity. The mean of the 21 overall industry Gini coefficients is large ($m = 0.60$), and the standard deviation relatively small ($s = 0.12$). The overall Ginis range widely across industries (from 0.74 (computers) to 0.27 (motor vehicles)), suggesting some pairwise differences, but in 17 of 21 industries the Ginis fall between 0.56 and 0.74. Of the 105 Ginis, only one (1-year investor return in soft drinks) produced perfect parity (Gini = 0).

The results do vary significantly across performance measures, with very large Ginis for profits

Table 1. Gini coefficients: 1980–99

Industry	n	Profitability			Investor yield		Overall
		Profit Gini	ROS Gini	ROE Gini	1-yr Gini	10-yr Gini	Industry mean
Mining and crude oil production	14	0.51	0.32	0.51	0.35	0.64	0.47
Foods	50	0.75	0.91	0.68	0.28	0.82	0.69
Textiles	13	0.62	0.51	0.52	0.30	0.54	0.50
Apparel	12	0.88	0.72	0.58	0.35	0.54	0.61
Publishing and printing	18	0.94	0.69	0.76	0.52	0.68	0.72
Chemicals	40	0.96	0.48	0.49	0.41	0.60	0.59
Petroleum refining	27	1.00	0.72	0.54	0.47	0.76	0.70
Aerospace	13	0.83	0.72	0.70	0.16	0.52	0.59
Pharmaceuticals	15	0.95	0.81	0.77	0.37	0.75	0.73
Toys and sporting goods	5	0.65	0.52	0.72	0.30	0.67	0.57
Motor vehicles	3	0.35	0.30	0.10	0.10	0.50	0.27
Computers	25	0.98	0.76	0.65	0.59	0.72	0.74
Brewing	3	1.00	0.85	0.80	0.35	0.65	0.73
Rubber and plastic products	12	0.93	0.60	0.46	0.35	0.74	0.62
Industrial and farm equipment	32	0.90	0.57	0.48	0.27	0.78	0.60
Metal products	19	0.94	0.75	0.69	0.36	0.69	0.69
Scientific and photographic equipment	16	0.95	0.74	0.63	0.07	0.64	0.61
Forest and paper products	36	0.89	0.62	0.65	0.09	0.74	0.60
Metals	20	0.85	0.67	0.48	0.12	0.70	0.56
Soft drinks	2	1.00	1.00	0.80	0.00	0.20	0.60
Transportation equipment	8	0.34	0.39	0.39	0.39	0.41	0.38
Median	15.00	0.90	0.69	0.63	0.35	0.67	0.60
Mean	18.24	0.82	0.65	0.59	0.30	0.63	0.60
S.D.	12.82	0.21	0.18	0.17	0.15	0.14	0.12

Overall results: $n = 105$ Gini coefficients

Median Gini	0.64
Mean Gini	0.60
Standard deviation	0.24

(mean = 0.82), and smaller coefficients for 1-year investor returns (mean = 0.35). Neither of these findings is surprising, and they support the construct validity of the Ginis. Absolute profit correlates with firm size, and the same large competitors tend to maintain profit dominance. For example, IBM, the largest computer firm, led the computer industry in profit in 17 of 20 years, but led only six times in ROS. Similarly, Dupont, the largest chemicals firm, led in profits 15 of 20 years, but never led in ROS.

By contrast, 1-year returns to investors is the measure most likely to resemble a random walk, and the Ginis are accordingly lowest for this measure. In five industries—foods (Gini = 0.28), industrial and farm equipment (0.27), metal products (0.12), forest products (0.09), and scientific and photographic equipment (0.07)—no firm led its industry in 1-year investor returns more than twice. The same does not hold for 10-year investor returns, which, like profit, are serially correlated by definition. Offsetting the random properties of stock prices (which tend to suppress Ginis) with a carryover of prior-period outcomes (which enhances them), the 10-year yields produced results resembling those of the profit rate measures.

The empirical Ginis raise questions at the heart of strategy research: How do we explain firm performance disparities? Why do the disparities vary across industries? Can the disparities be attributed to economic and strategic variables (concentration, collusion, product differentiability, firm conduct, firm resources, etc.)? For the moment, however, we defer these questions—if perfect parity is empirically improbable, and if some measures are serially correlated for obvious reasons, then perfect parity is not a solid foundation for theory-building or empirical analysis.

Hypothesis 2: Stochastic parity

Hypothesis 2 compares empirical Gini coefficients with those obtained using random distributions of wins (the simulation model and z-score computation were as described earlier). Table 2 shows the results for industry sizes corresponding to the *Fortune* 500 data. For example, for $n = 5$ (toys and sporting goods), the simulation produced 10,000 Ginis with mean $= 0.28$, and standard deviation 0.10.[1] For $n = 14$ (mining and crude oil production), the mean was 0.45, and the standard deviation 0.08. In general, the simulated Ginis increase in the range from $n = 2$ firms (mean Gini $= 0.18$) through $n = 20$ (mean Gini $= 0.52$), then decline slowly as n rises.[2]

Table 3 shows z-scores for all industries and performance measures. Whereas 18 of the 21 industries had overall Ginis of at least 0.50, only eight of the 21 coefficients produced statistically significant z-scores at $a < 0.01$. The z-scores indicate significant variation by industry, with five industries producing z-scores below $+1$ (mining and crude oil production, textiles, motor vehicles, metals and transportation equipment), and five producing z-scores above $+3$ (foods, pharmaceuticals, computers, brewing, and soft drinks). The results also vary by performance measure, with overall means ranging from $z = +4.50$ (for profit) to $z = -1.11$ (1-year return to investors), and two of the five measures (profit and ROS) significant at $a < 0.01$.

Stochastic parity can be defined as performance consistent with random processes, and Hypothesis 2 is supported if the z-scores are generally large and statistically significant. Overall, the results support Hypothesis 2, doing little to refute a presumption of widespread, persistent disparities in firm performance. Of the 105 Ginis, 87 (82.9% of the total) were positive, and 49 (46.7%) were statistically significant at $a < 0.01$. The Wilcoxon rank-sum test, which gives a z-score based on ranking the 105 obtained Ginis in the same array as the simulated Ginis, is highly significant ($z = +7.00$), and points to the operation of causal forces beyond random performance assignments.

Table 2. Expected Gini coefficients

Industry	Simulated Gini coefficients (10,000 trials)		
	n	Mean	S.D.
Mining and crude oil production	14	0.45	0.08
Foods	50	0.29	0.11
Textiles	13	0.44	0.09
Apparel	12	0.42	0.09
Publishing and printing	18	0.51	0.08
Chemicals	40	0.34	0.10
Petroleum refining	27	0.44	0.09
Aerospace	13	0.44	0.09
Pharmaceuticals	15	0.47	0.08
Toys and sporting goods	5	0.28	0.10
Motor vehicles	3	0.22	0.11
Computers	25	0.47	0.09
Brewing	3	0.22	0.11
Rubber and plastic products	12	0.42	0.09
Industrial and farm equipment	32	0.40	0.10
Metal products	19	0.52	0.08
Scientific and photographic equipment	16	0.48	0.08
Forest and paper products	36	0.37	0.10
Metals	20	0.53	0.08
Soft drinks	2	0.18	0.14
Transportation equipment	8	0.35	0.09
Median	15.00	0.42	0.09
Mean	18.24	0.39	0.09
S.D.	12.82	0.10	0.01

As variations on stochastic parity, and in an attempt to approximate the obtained Ginis, we simulated three additional conditions. Unlike Model 1, which assumes random performance assignments in each period (independence across periods), Models 2, 3, and 4 are 'contagion' models, in which performance is not independent from period to period. The models assume each industry has the same quantity of a causal factor x (set at 20 units), which is allocated randomly, one unit at a time, so that each firm's probability of receiving a unit of x is $1/n$ in each allocation. In all industries with $n > 20$, a maximum of 20 firms can receive units of x. In all three models, a firm's probability of a 'win' for any year is proportionate to its stock of x at the beginning of that year. In Model

[1] The Ginis approximated normal distributions for all n except $n = 2$, which had the highest probability of zero Gini (0.18) and was positively skewed.

[2] The pattern for $n > 20$ firms is an artifact of the nondivisibility of wins, combined with the arbitrary selection of period $t =$ 20 years: when the number of firms exceeds 20, the mean wins per firm ($20/n$) is less than one; since no firm can achieve a partial win, zero Gini would be unattainable for $n > 20$. Thus, where $n > 20$, perfect parity occurs not when all n firms win t/n times, but when 20 different firms win once over the period. Because the probability that any firm will win more than once declines as n rises, the simulated Ginis decline as n exceeds 20.

Table 3. Deviations from stochastic parity

Industry	z-scores						
		Profitability			Investor yield		Overall
	n	Profit	ROS	ROE	1-yr	10-yr	mean
Mining and crude oil production	14	0.75	−1.63	0.75	−1.25	2.37	0.20
Foods	50	**4.18**	**5.64**	**3.54**	−0.09	**4.82**	**3.62**
Textiles	13	2.00	0.78	0.89	−1.56	1.11	0.64
Apparel	12	**5.11**	**3.33**	1.78	−0.78	1.33	2.15
Publishing and printing	18	**5.37**	2.25	**3.12**	0.12	2.12	**2.60**
Chemicals	40	**6.20**	1.40	1.50	0.70	**2.60**	2.48
Petroleum refining	27	**6.22**	**3.11**	1.11	0.33	**3.56**	**2.87**
Aerospace	13	**4.33**	**3.11**	**2.89**	**−3.11**	0.89	1.62
Pharmaceuticals	15	**6.00**	**4.25**	**3.75**	−1.25	**3.50**	**3.25**
Toys and sporting goods	5	**3.70**	2.40	**4.40**	0.20	**3.90**	**2.92**
Motor vehicles	3	1.18	0.73	−1.09	−1.09	2.54	0.45
Computers	25	**5.67**	**3.22**	2.00	1.33	**2.78**	**3.00**
Brewing	3	**7.09**	**5.73**	**5.27**	1.18	**3.91**	**4.64**
Rubber and plastic products	12	**5.67**	2.00	0.44	−0.78	**3.56**	2.18
Industrial and farm equipment	32	**5.00**	1.70	0.80	−1.30	**3.80**	2.00
Metal products	19	**5.25**	**2.87**	2.13	−2.00	2.12	2.07
Scientific and photographic equipment	16	**5.88**	**3.25**	1.88	**−5.12**	2.00	1.58
Forest and paper products	36	**5.20**	2.50	**2.80**	**−2.80**	**3.70**	2.28
Metals	20	**4.00**	1.75	−0.63	**−5.12**	2.12	0.42
Soft drinks	2	**5.86**	**5.86**	**4.43**	−1.29	0.14	**3.00**
Transportation equipment	8	−0.11	0.44	0.44	0.44	0.67	0.38
Median	15.00	5.20	2.50	1.88	−1.09	2.54	2.18
Mean	18.24	**4.50**	**2.60**	2.01	−1.11	2.55	2.11
S.D.	12.82	1.97	1.83	1.69	1.78	1.25	1.19
Wilcoxon rank-sum z-score		**4.73**	**4.20**	**4.19**	−2.16	**4.63**	3.43

Overall results (105 z-scores)

Median z-score	2.12
Median z-score	2.11
Standard deviation z-score	2.49
Wilcoxon rank-sum z-score	7.00

Note: Values in bold type are statistically significant at a <0.01 (two-tailed).

2, we assume that the initial distribution of x persists throughout the 20-year period; in Model 3 we assume that a win bestows a new unit of x, so that the proportions of x change each period (to the marginal benefit of the latest winner), with the total stock of x after 20 periods increasing to 40 units; in Model 4, we assume a moving window of 20-year periods, so that wins occurring more than 20 periods previously have no bearing on current probabilities.[3] More descriptively: Model 2 simulates a world of competitive focal points, in which advantages, once achieved, determine long-term performance; Model 3 entails a growing stock of advantages and ever-evolving allocations across firms; and Model 4 simulates a world in which total advantage remains constant, but firm-specific advantages are redistributed in the long run.

The results are shown in Table 4, and suggest two observations. First, Models 2 and 3 are not inconsistent with the *Fortune* data—under Model 2, the data show slightly more disparity than the simulation, and under Model 3 slightly more parity. Neither model would allow us to reject the assumption of randomly assigned performance causes that, over a period of 20 years, are highly resistant to redistribution—fixed and

[3] Models 2, 3, and 4 are contagion conditional probability models resembling 'Polya's urn model,' in which prior outcomes modify successive probabilities. Similar models are associated with Bose–Einstein statistics in physics, explaining the empirical frequency of particle distributions (see Feller, 1968; Hill, 1974; Ross, 1993).

Table 4. Stochastic Models 2, 3 and 4

Industry	Actual Gini	Overall industry performance					
		Model 2		Model 3		Model 4	
		Sim Gini	Industry z-score	Sim Gini	Industry z-score	Sim Gini	Industry z-score
Mining and crude oil production	0.47	0.59	−1.50	0.68	**−2.62**	0.80	**−4.71**
Foods	0.69	0.59	1.43	0.71	−0.29	0.84	−2.50
Textiles	0.50	0.58	−1.00	0.67	−1.89	0.79	**−4.14**
Apparel	0.61	0.56	0.62	0.65	−0.44	0.77	−2.00
Publishing and printing	0.72	0.66	1.00	0.73	−0.14	0.84	−2.40
Chemicals	0.59	0.60	−0.14	0.71	−1.71	0.84	**−5.00**
Petroleum refining	0.70	0.64	0.86	0.73	−0.43	0.85	**−3.00**
Aerospace	0.59	0.58	0.12	0.67	−0.89	0.79	**−2.86**
Pharmaceuticals	0.73	0.61	1.71	0.69	0.05	0.81	−1.33
Toys and sporting goods	0.57	0.37	1.67	0.45	0.86	0.57	0.00
Motor vehicles	0.27	0.28	−0.08	0.35	−0.47	0.47	−0.95
Computers	0.74	0.65	1.29	0.74	0.00	0.85	−2.20
Brewing	0.73	0.28	**3.46**	0.35	2.23	0.47	1.23
Rubber and plastic products	0.62	0.56	0.75	0.65	−0.33	0.77	−1.87
Industrial and farm equipment	0.60	0.62	−0.29	0.72	−1.71	0.84	**−4.80**
Metal products	0.69	0.67	0.33	0.74	−0.71	0.84	**−3.00**
Scientific and photographic equipment	0.61	0.63	−0.29	0.71	−1.43	0.82	**−3.50**
Forest and paper products	0.60	0.61	−0.14	0.72	−1.71	0.84	**−4.80**
Metals	0.56	0.68	−2.00	0.76	**−3.33**	0.85	**−5.80**
Soft drinks	0.60	0.22	2.23	0.29	1.48	0.39	0.81
Transportation equipment	0.38	0.47	−0.90	0.56	−1.50	0.69	**−2.82**
Median	0.60	0.59	0.33	0.69	−0.47	0.81	**−2.82**
Mean	0.60	0.55	0.43	0.63	−0.71	0.75	**−2.65**
Standard deviation	0.12	0.14	1.29	0.14	1.30	0.14	1.90
Wilcoxon rank-sum z-score		−1.23		1.71		**3.60**	

Summary of models

All models:	Advantages distributed randomly; performance proportional to advantages
Model 2:	Stock of industry advantages fixed; initial distribution of advantages persists throughout
Model 3:	Stock of industry advantages doubles over 20 years; distribution of advantages adjusted for recent performance
Model 4:	Industry advantages fixed; distribution adjusted for recent performance; advantages decay

Note: Values in bold type are statistically significant at $a < 0.01$ (two-tailed).

perfectly resistant in Model 2; growing and imperfectly resistant in Model 3. Second, Model 4 is not consistent with the data, though it fits well for some industries. Based on the *Fortune* data, we would conclude that most empirical distributions display significantly less dominance than produced by Model 4 assumptions.

Hypothesis 3: Pareto parity

Pareto's law, with $a = 1.5$, produces a distribution in which wins for the leading firm are in the proportion $r^{1.5}$ to 1 to those of a firm ranked r, i.e., the leading firm's wins are $2^{1.5}$ (roughly 2.83) times greater than those of the second-ranked firm. Finding the Pareto number of wins in an industry requires the value of c that sums all firms' wins to 20, i.e., $c = \left(20\sum_{r=1}^{n} r^{-1.5}\right)^{-1}$. For $n = 5$ firms, $c = 11.36$, with $(11.36)/(2^{1.5}) = 4.02$ wins for the second-leading firm, etc. The corresponding Gini for $n = 5$ is 0.58.

It is important to note that Pareto's law and its variants manifest themselves across very large samples (of words, cities, species, etc.) which, for all practical purposes, are distributed continuously. As such, 20 discrete observations of firm performance do not constitute a sufficient test of Pareto's law. The Pareto distribution, like other skew distributions, is what Ijiri and Simon termed an 'extreme hypothesis,' i.e., a broad-form null model not explicitly confirmable, but subject to rejection and theoretical refinement. If the data do not disconfirm the proposed form, then more specific forms and underlying logics can be investigated. In the present context, it was possible to calculate theoretical Ginis corresponding to alternative values of a (e.g., $a = 1.0$), in order to consider whether observed Ginis are consistent with any power law. But again, the distribution $f = cr^{-1.5}$ does not uniquely define Gini = 0.58. Other distributions can produce the same Gini, and the standard error of estimate for $t = 20$ is too large to warrant statistical conclusions about whether any power law describes the data.

Hypothesis 3 hypothesizes that the obtained z-scores will differ significantly from Pareto's law with $a = 1.5$, and this appears to be supported in Table 5—there is less competitive dominance in the *Fortune* data than predicted in the Pareto model. Table 5 presents Ginis for two variants of Pareto's parity—$a = 1.0$ and $a = 1.5$—and shows distributions of wins for $n = 2$, 5, 10, 20, and 40 firms. The results can be interpreted by comparing the Pareto z-scores to the *Fortune* data. In earlier comparisons to stochastic Model 1, the *Fortune* z-scores for overall performance were independent of industry size ($r_{z,n} = 0.19$), allowing comparisons of observed z-scores with those obtained from Pareto models. The data in Table 5 confirm that the *Fortune* z-scores are generally lower than those under the $a = 1.5$ Pareto model, and generally higher that those under the model $a = 1.0$. In iterating to a model of best fit, the a value best fitted to the data is roughly $a = 1.25$.

We noted earlier that, although no cross-disciplinary consensus has emerged on the causes of power laws, Ijiri and Simon have shown, in research on the size distributions of firms, that the exponent a can be interpreted as a function of entry conditions. Specifically, where p is the probability that the next unit of growth (by analogy, a 'win') is assigned to a new entrant, then a can be computed as $a = (1 - p)^{-1}$. In the Ijiri–Simon simulations, entry and exit had no impact on whether the distributions took on the Pareto form, but only affected the value of the exponent a (i.e., greater net entry increases a since more new firms led to greater performance disparity, which follows from their lower probability of future wins). Moreover, the Pareto-like distributions were robust limiting forms, arising irrespective of initial endowments (e.g., of firm size).

Table 5. Pareto parity

Rank	$r^{-1.0}$	$a = 1.0$					$r^{-1.5}$	$a = 1.5$				
		Firsts $n = 2$	Firsts $n = 5$	Firsts $n = 10$	Firsts $n = 20$	Firsts $n = 40$		Firsts $n = 2$	Firsts $n = 5$	Firsts $n = 10$	Firsts $n = 20$	Firsts $n = 40$
1	1.000	13.33	8.76	6.84	5.56	4.60	1.000	14.78	11.37	10.03	9.22	8.65
2	0.500	6.67	4.38	3.42	2.78	2.30	0.353	5.22	4.01	3.54	3.26	3.05
3	0.333		2.92	2.25	1.85	1.53	0.192		2.18	1.93	1.77	1.66
4	0.250		2.19	1.71	1.39	1.15	0.125		1.42	1.26	1.15	1.08
5	0.200		1.75	1.37	1.11	0.92	0.089		1.02	0.89	0.82	0.77
6	0.167			1.14	0.93	0.77	0.068			0.68	0.63	0.59
7	0.143			0.98	0.79	0.66	0.054			0.54	0.50	0.47
8	0.125			0.85	0.69	0.57	0.044			0.44	0.40	0.38
9	0.111			0.76	0.62	0.51	0.037			0.37	0.34	0.32
10	0.100			0.68	0.56	0.46	0.032			0.32	0.30	0.28
11	0.091				0.51	0.42	0.027				0.25	0.23
12	0.083				0.46	0.38	0.024				0.22	0.21
13	0.077				0.43	0.35	0.021				0.19	0.18
14	0.071				0.39	0.33	0.019				0.18	0.16
15	0.067				0.37	0.31	0.017				0.16	0.15
16	0.063				0.35	0.29	0.016				0.15	0.14
17	0.059				0.33	0.27	0.014				0.13	0.12
18	0.056				0.31	0.26	0.013				0.12	0.11
19	0.053				0.29	0.24	0.012				0.11	0.10
20	0.050				0.28	0.23	0.011				0.10	0.09
Sum	3.599	20.00	20.00	20.00	20.00	16.55	2.168	20.00	20.00	20.00	20.00	18.74
Gini		0.33	0.41	0.46	0.52	0.51		0.48	0.58	0.66	0.74	0.79
z-score (Model 1)		1.07	1.30	0.78	−0.14	2.89		2.14	3.00	3.00	3.00	4.50
Mean z-score				**1.18**						**3.13**		
Fortune mean z-score							**2.11**					

This supports the hypothesis that firm performance, like firm size, follows a proportional growth heuristic. This would be consistent with our findings for stochastic parity, in which performance did not conform to Model 1 stochastic parity (random outcomes), but resembled stochastic Models 2 and 3, which assume performance proportional to past wins. It may also be possible to explain tentatively why the ideal zero-entry model ($a = 1$) slightly understates the model of best fit ($a \approx 1.25$). The simplest explanation is that three of the five performance measures do not obey proportional growth processes—for profit and 10-year investor returns, $a = 1$ should be an underestimate, and for 1-year returns $a = 1$ should be an overestimate. Second, as noted earlier, the Ginis assume zero entry, even though firms do move on and off the *Fortune* lists at the margins. As such, the probability of a 'first' by a new entrant was small, but nonzero (this would also explain the slight negative bias in Ginis for 1-year investor returns). To fit $a = 1.25$ would require a new entry probability of 0.20, or roughly three new firms entering a *Fortune* industry of 18 competitors. This rate of entry is slightly higher on average than the turnover of *Fortune* 500 firms, but would account for the obtained departure from $a = 1$.

Hypothesis 4: Natural parity

To compare business and nonbusiness distributions, we gathered 20-year performance data in a variety of nonindustrial competitive domains (sports, games, politics, etc.), and computed Ginis using the same method applied to the *Fortune* data. The data were drawn from various databases, journals, books, almanacs, and web sites, and the domains included team sports, individual sports, politics, games (billiards, bridge, chess), and entertainment. No systematic sampling pattern was used, aside from an implicit preference for accessible data. Table 6 shows the 107 obtained Ginis, simulated Ginis under stochastic Model 1, and the corresponding z-scores.

Hypothesis 4 predicted that the industry z-scores would differ significantly from those in the nonbusiness domains. Table 7 summarizes the Table 6 data, with comparisons to the *Fortune* data. Hypothesis 4 was not supported: the nonindustrial data produced 107 Ginis with mean = 0.56, compared to 0.60 for the 105 *Fortune* Ginis, and their standard deviations (0.24) were the same. The mean nonindustrial z-score was +2.44, compared to +2.11 in the *Fortune* data, and their standard deviations were comparable (2.20 and 2.49, respectively). The Wilcoxon rank-sum test produced an overall z-score of +7.38 in the nonindustrial data, compared to +7.00 in the *Fortune* data.

Clearly, the nonindustrial statistics strongly resemble those in the *Fortune* data, and it would be of great theoretical interest to explain this resemblance (a naïve hypothesis is that performance z-scores have mean of about +2 in relation to a stochastic parity null). The final section of the paper offers further theoretical and empirical directions for such research. For now, it seems reasonable to suggest that firm performance distributions are not unique in the competitive landscape, and that there exists some level of 'natural parity' (or 'ordinary disparity') which researchers working from conventional stochastic models would not observe, and may attribute to industry- or firm-specific factors. At a minimum, the data suggest that firm performance adheres to substantially the same empirical pattern as performance in other domains.

RECAPITULATION

The paper investigates the consequences of using winning as the dependent variable, and explores the theme that researchers' interpretations of firm performance depend on their models of competitive parity. If researchers expect perfect parity (Hypothesis 1), they find rampant performance disparities, and require large-scale auxiliary models to explain discrepancies between theory and fact (e.g., the theory of perfect competition requires theories of monopoly, oligopoly, monopolistic competition, etc.). If researchers are prepared for randomly generated performance disparities (Hypothesis 2), then the facts are less jarring, and explanations will tend to emphasize extreme cases. If researchers suspect underlying proportional growth processes, they postulate skew distributions (Hypothesis 3), and study departures from simple growth and entry heuristics; and if they posit nonindustrial benchmarks, they study deviations from 'natural parity' (Hypothesis 4), making structural comparisons across business and nonbusiness domains.

Table 6. Nonindustrial domains

Domain	*n*	SIMULATED		ACTUAL	
		Mean	S.D.	Gini	*z*-score
World Chess Championship 1886–1952	75	0.21	0.11	0.84	**5.73**
World Chess Championship 1955–98	75	0.21	0.11	0.77	**5.09**
Australian Chess Championship 1924–67	40	0.34	0.10	0.67	**3.30**
U.S. Chess Championship 1960–79	50	0.29	0.11	0.83	**4.91**
Wimbledon (tennis): men's singles title 1979–98	100	0.16	0.10	0.70	**5.40**
Wimbledon (tennis): women's singles title 1979–98	60	0.25	0.11	0.86	**5.55**
Wimbledon (tennis): men's singles title 1959–78	100	0.16	0.10	0.60	**4.40**
Wimbledon (tennis): women's singles title 1959–78	60	0.25	0.11	0.72	**4.27**
Davis Cup tennis 1969–88	12	0.42	0.09	0.84	**4.67**
Davis Cup tennis 1949–68	10	0.39	0.09	0.78	**4.33**
NCAA college football AP rank 1977–96	80	0.20	0.10	0.60	**4.00**
NCAA college football AP rank 1957–76	80	0.20	0.10	0.56	**3.60**
Academy Award: best actor 1971–90	250	0.07	0.08	0.10	0.38
Academy Award: best actor 1951–70	250	0.07	0.08	0.00	−0.88
Academy Award: best actress 1971–90	250	0.07	0.08	0.19	1.50
Academy Award: best actress 1951–70	250	0.07	0.08	0.19	1.50
Academy Award nominations by studio 1957–76	10	0.39	0.09	0.58	2.11
Miss America 1980–99	50	0.29	0.11	0.27	−0.18
Miss America 1960–79	50	0.29	0.11	0.42	1.18
Pulitzer Prize national reporting 1965–84	50	0.29	0.11	0.34	0.45
Pulitzer Prize international reporting 1965–84	30	0.41	0.09	0.52	1.22
Pulitzer Prize commentary 1970–89	50	0.29	0.11	0.44	1.36
Top ten albums and singles by record company 1960–79	50	0.29	0.11	0.66	**3.36**
National Football League: Super Bowl 1967–86	28	0.43	0.09	0.69	**2.89**
PGA Tour money winnings (golf) 1980–99	130	0.15	0.10	0.56	**4.10**
PGA Tour money winnings (golf) 1960–79	60	0.25	0.11	0.80	**5.00**
PGA Tour money winnings (golf) 1939–59	50	0.29	0.11	0.56	2.45
European Order of Merit rank (golf) 1971–90	100	0.16	0.10	0.75	**5.90**
Ryder Cup (golf) 1927–73	2	0.18	0.14	0.70	**3.71**
Women's U.S. Open Golf Championship 1977–96	80	0.20	0.10	0.42	2.20
Women's U.S. Open Golf Championship 1957–76	80	0.20	0.10	0.59	**3.90**
British Women's Open Golf Championship 1976–96	80	0.20	0.10	0.10	−1.00
Walker Cup (golf) 1957–95	2	0.18	0.14	0.70	**3.71**
Men's U.S. Amateur Golf Championship 1977–96	80	0.20	0.10	0.28	0.80
Men's British Amateur Golf Championship 1977–96	60	0.25	0.11	0.10	−1.36
Australian Women's Amateur Golf Championship 1948–67	60	0.25	0.11	0.50	2.27
Australian Men's Amateur Golf Championship 1948–67	80	0.20	0.10	0.27	0.70
MLB American League wins 1961–80	12	0.42	0.09	0.71	**3.22**
MLB American League wins 1941–60	8	0.35	0.09	0.77	**4.67**
MLB National League wins 1969–88	12	0.42	0.09	0.61	2.11
MLB National League wins 1949–68	10	0.39	0.09	0.67	**3.11**
World Cup Baseball 1953–98	30	0.41	0.09	0.98	**6.33**
National Basketball Association wins 1979–98	27	0.44	0.09	0.81	**4.11**
National Basketball Association wins 1959–78	14	0.45	0.08	0.78	**4.13**
NBA Most Valuable Player Award 1970–89	100	0.16	0.10	0.72	**5.60**
Big East basketball wins 1979–98	10	0.39	0.09	0.53	1.56
NCAA Men's basketball champions 1970–89	100	0.16	0.10	0.62	**4.60**
NCAA Men's basketball champions 1950–69	100	0.16	0.10	0.56	**4.00**
Sheffield Shield Australian cricket wins 1956–75	5	0.28	0.10	0.33	0.50
English County Cricket 1906–29	16	0.48	0.08	0.78	**3.75**
National Hockey League Stanley Cup 1974–93	20	0.53	0.08	0.83	**3.75**
National Hockey League Stanley Cup 1954–73	12	0.42	0.09	0.84	**4.67**
VFL Australian football titles 1899–1918	12	0.42	0.09	0.61	2.11
VFL Australian football titles 1932–51	12	0.42	0.09	0.55	1.44
VFL Australian football titles 1960–79	9	0.37	0.09	0.55	2.00
Olympic summer games medal count 1896–1984	60	0.25	0.11	0.93	**6.18**

Table 6. (*Continued*)

Domain	*n*	SIMULATED		ACTUAL	
		Mean	S.D.	Gini	*z*-score
Women's World Figure Skating Championships 1970–89	25	0.47	0.09	0.49	0.22
Men's World Figure Skating Championships 1970–89	25	0.47	0.09	0.59	1.33
Women's U.S. Outdoor Speed Skating Championship 1970–89	30	0.41	0.09	0.35	−0.67
Men's U.S. Outdoor Speed Skating Championship 1970–89	30	0.41	0.09	0.14	**−3.00**
Men's World Cup Alpine Skiing—overall points 1969–88	40	0.34	0.10	0.70	**3.60**
Women's World Cup Alpine Skiing—overall points 1969–88	40	0.34	0.10	0.66	**3.20**
Australian Men's Handball Championship 1948–67	25	0.47	0.09	0.81	**3.78**
U.S. Men's Handball Champion (singles) 1970–89	40	0.34	0.10	0.86	**5.20**
U.S. Men's Handball Champion (doubles) 1960–79	40	0.34	0.10	0.72	**3.80**
U.S. professional rodeo: All-Around Cowboy 1969–88	20	0.53	0.08	0.66	1.63
Australian Women's Field Hockey Champion 1946–66	5	0.28	0.10	0.85	**5.70**
Australian Women's High Diving Champion (10 m) 1949–68	16	0.48	0.08	0.73	**3.13**
Australian Men's High Diving Champion (10 m) 1949–68	20	0.53	0.08	0.65	1.50
U.S. Presidential elections by party 1920–96	2	0.18	0.14	0.00	−1.29
U.S. Presidential elections by party 1840–1916	3	0.22	0.11	0.35	1.18
U.S. Senate majority party 87th–106th Congress: 1961–99	2	0.18	0.14	0.40	1.57
U.S. Senate majority party 67th–86th Congress: 1921–60	2	0.18	0.14	0.15	−0.21
U.S. House of Reps. majority party 87th–106th Congress: 1961–99	2	0.18	0.14	0.70	**3.71**
U.S. House of Reps. majority party 67th–86th Congress: 1921–60	2	0.18	0.14	0.20	0.14
U.S. state governors by party 1980–99	2	0.18	0.14	0.50	**2.29**
U.S. state governors by party 1960–79	2	0.18	0.14	0.65	**3.36**
Australian prime minister by party, ministries 38–57: 1968–99	2	0.18	0.14	0.00	−1.29
Australian House of Representatives by majority party 1940–87	2	0.18	0.14	0.90	**5.14**
Australian Senate by majority party 1940–87	2	0.18	0.14	0.00	−1.29
English Women's Snooker Champions 1961–80	20	0.53	0.08	0.72	2.38
English Men's Amateur Snooker Championship 1966–85	40	0.34	0.10	0.42	0.80
English Men's Amateur Snooker Championship 1946–65	40	0.34	0.10	0.49	1.50
Maltese Amateur Snooker Championship 1950–69	20	0.53	0.08	0.92	**4.88**
Welsh Amateur Snooker Championship 1965–84	20	0.53	0.08	0.63	1.25
Australian Amateur Snooker Championship 1965–84	30	0.41	0.09	0.76	**3.89**
Australian Amateur Billiards Championship 1935–60	20	0.53	0.08	0.95	**5.25**
World Snooker Championship 1965–85	80	0.20	0.10	0.77	**5.70**
Women's bridge champions (pairs): U.S. Spring Nationals 1951–70	12	0.42	0.09	0.36	−0.67
Team bridge champions: U.S. Spring Nationals 1951–70	12	0.42	0.09	0.51	1.00
Women's bridge champions (pairs): All-America Regionals 1948–70	12	0.42	0.09	0.19	−2.56
American Bridge Assoc. Championships (open pairs): 1950–70	16	0.48	0.08	0.48	0.00
U.S. Women's IBC bowling champion 1965–84	40	0.34	0.10	0.10	−2.40
Men's Professional Bowler's Association champion 1965–84	60	0.25	0.11	0.62	**3.36**
U.S. intercollegiate rowing champion 1950–69	30	0.41	0.09	0.80	**4.33**
U.S. intercollegiate rowing champion 1970–89	30	0.41	0.09	0.69	**3.11**
U.S. NCAA lacrosse champion 1970–89	30	0.41	0.09	0.84	4.78
U.S. amateur fast-pitch softball champions 1969–89	80	0.20	0.10	0.34	1.40
U.S. harness racing champion drivers 1967–86	15	0.47	0.08	0.62	1.88
Kentucky Derby winning jockey 1940–59	12	0.42	0.09	0.43	0.11
Kentucky Derby winning jockey 1960–79	12	0.42	0.09	0.43	0.11
World Grand Prix driving champion 1969–88	15	0.47	0.08	0.58	1.38
Indianapolis 500 champion 1956–75	20	0.53	0.08	0.42	−1.38
Australian Ladies Badminton Championships 1947–66	16	0.48	0.08	0.70	**2.75**
Australian clay target shooting champion 1948–67	25	0.47	0.09	0.35	−1.33
Australian Sailing Championship (18-foot class) 1948–67	20	0.53	0.08	0.80	**3.38**
Australian Star Class Sailing Championship 1947–67	20	0.53	0.08	0.74	**2.63**
All nonindustrial domains: n = 107 Ginis					
Median	27.00	0.34	0.10	0.61	2.63
Mean	43.17	0.32	0.10	0.56	2.44
S.D.	50.56	0.13	0.02	0.24	2.20

Table 7. Natural parity

Gini coefficients	Industrial domains (105 Ginis)	Nonindustrial domains (107 Ginis)	Diff.
Median	0.64	0.61	0.03
Mean	0.60	0.56	0.04
S.D.	0.24	0.24	0.00
z-scores			
Median z-score	2.12	2.63	−0.51
Mean z-score	2.11	2.44	−0.33
S.D. z-score	2.49	2.20	0.29
Wilcoxon rank-sum test (z-score)	7.00	7.38	−0.38
Overall Wilcoxon rank-sum test (for difference in z across domains)			0.60

Table 8. Summary of parity models

Parity model	Key assumption
Perfect parity	All firms perform the same
Stochastic parity	
Model 1	Performance is random
Model 2	Performance causes are random and fixed
Model 3	Performance causes are random and growing
Model 4	Performance causes are random and decaying
Pareto parity	
Model $a = 1.0$	Performance grows proportionally; follows $f = cr^{-1.0}$
Model $a = 1.5$	Performance grows proportionally; follows $f = cr^{-1.5}$
Natural parity	Performance similar across competitive domains

Table 8 summarizes the four models' key assumptions, and Figure 2 compares the models, indicating their tendencies to retain or reject the null. The upper area of Figure 2 shows the distribution of all 212 z-scores in the study: 105 from the industry data (five measures, 21 industries) and 107 from the nonindustrial data. The z-scores were taken relative to the random assignment of performance (as shown in Tables 3 and 6). The lower area shows how the various models would interpret these data; at the extremes, there is a large area of rejection on grounds of performance disparity in the perfect parity model (and no possible rejection on grounds of abnormal parity); whereas the natural parity model tolerates a wider band of performance variance, with smaller areas of rejection for abnormal disparity and parity. The other models provide alternative interpretations as discussed earlier.

Each of the four models has potential applications (e.g., for different domains or performance measures), and each produces its own theoretical and empirical emphases. Applications to the *Fortune* data have indicated their comparative analytical properties and the strengths and weaknesses of each model. This final section pulls together loose threads from earlier sections into four integrative observations: on future research, the theory of natural parity, industry vs. firm-specific advantage, and the role of extreme cases in the theory of competitive advantage.

Future research

Reconceptualizing performance as win frequencies presents empirical and theoretical opportunities for researchers, of which only a few could be explored here. To extend the present work, it would be possible in many of the domains to examine not only wins, but also a complete set of ranks, and thus to evaluate period-to-period performance decay. In prevailing strategy theories, superior performance arises from firm-specific

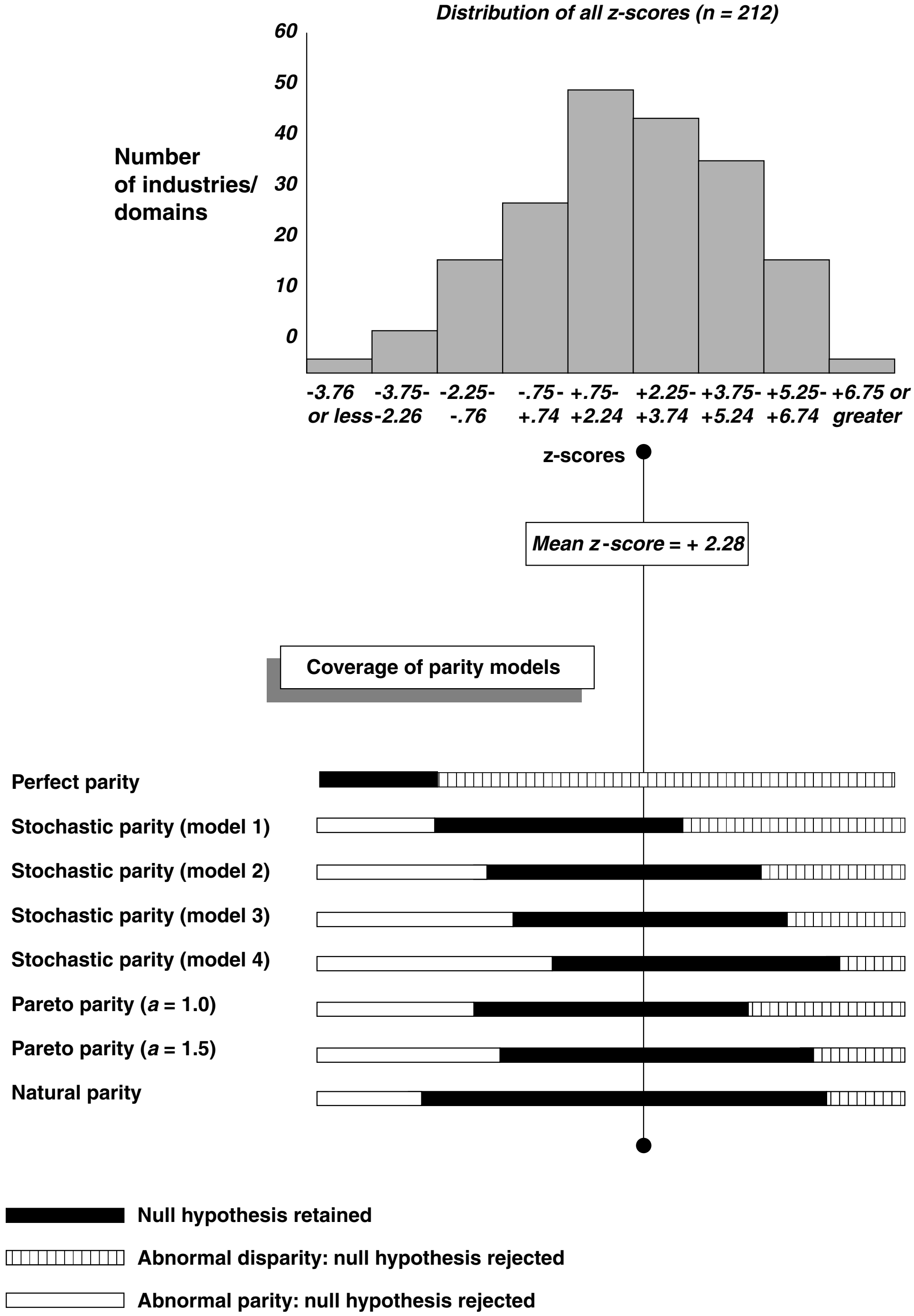


Figure 2. Parity models compared

resources or dynamic capabilities, but ranking the dependent variable enables us to untangle two very different performance components: significant Ginis in any given year (competitive dominance), and significant correlations between Ginis over 5-, 10-, or 20-year spans (persistence). These two components are conceptually independent. It would be possible, for example, to have performance persistence without competitive dominance—this requires only that performance ranks in an industry correlate over long periods, without significant Gini coefficients in any single year. The independence of dominance and persistence has not been widely recognized in strategy research, and raises important puzzles for strategy theory. For example, it would be of theoretical interest to consider whether, under a resource-based view, sustainable competitive advantages can coexist with competitive parity.

In the *Fortune* data, performance disparities varied significantly across measures. The paper has emphasized overall performance, but another reasonable next step is to show how different performance measures accommodate different parity models. The *Fortune* data suggest that total profits, and to some extent 10-year investor yields, follow a model resembling Pareto's law with $a = 1.5$, whereas ROS and ROE adhere more closely to a power law with $a = 1.25$, and 1-year investor returns are best explained by stochastic Model 1 (random performance). Overall performance resembles the patterns for ROS and ROE, but is, in fact, a linear combination of offsetting effects.

Subsequent research could take a given performance measure, say ROS, and compare outliers on that measure against some plausible parity model (for ROS, either stochastic Model 2 or 3, or Pareto Model $a = 1$). For example, neither stochastic Model 3 nor Pareto Model $a = 1$ can be rejected for the ROS distributions in 18 of 21 industries, leaving only the foods, brewing, and soft drink industries as outliers. These industries would comprise a research agenda on 20-year ROS, with other industries' distributions attributable to the proportional growth heuristic. Further investigation in foods, for example, would show that only five firms led the industry in ROS over the 20 years (the distribution was 9,8,1,1,1, with 45 firms without firsts)—Kellogg led the industry nine times and Wrigley eight times. In this industry, a presumption of nonrandom advantage seems warranted, and economic theories can be deployed with good effect, i.e., not to account for random performance disparities, or disparities attributable to simple heuristics, but to explain genuine economic anomalies. As it turns out, industrial organization and antitrust provide well-documented accounts of Kellogg's dominance through alleged limit pricing, exclusionary practices, and 'shared monopolization' of the ready-to-eat breakfast cereal industry (see, for example, Schmalansee, 1978; Scherer, 1979; Harris, 1979).

Researching natural parity

Table 9 shows the industrial and nonindustrial domains with the highest performance z-scores, i.e., the upper tail of the distribution in Figure 2; and Table 10 shows those with the lowest z-scores, i.e., the lower tails. Under a natural parity model, these extreme cases take on special significance, with the middle quartiles comprising more typical distributions. The juxtapositions in these tables highlight unusual but interesting performance questions such as: Why do Ginis for chess championships resemble Ginis for profit rates in the brewing industry? Why are Ginis higher in baseball than in politics (most of the time), but similar in baseball and the publishing industry? Why are Ginis higher in billiards than in horse-racing? Why are Ginis higher in chess than in Miss America pageants?

A potentially fruitful approach to these questions arises from the institutional considerations already discussed, and suggests the possibility of a broad, cross-domain performance framework grounded broadly in 'economic sociology' (Coase, 1988; Granovetter, 1985; Swedberg, Himmelstrand, and Brulin, 1990), and in the theory of distributional justice (Rawls, 1971; Nozick, 1974; Singer, 1978; Deutsch, 1985). We do not develop the theory here, but a clear requirement is to identify mechanisms that explain variations in parity across competitive domains, entailing industrial models as a special case. For example, chess produces higher z-scores than Miss America pageants because Miss America pageants suppress labor pool advantages (each state is allowed only one entrant), disable increasing returns to winning (states are required to send new contestants each year), and measure performance subjectively (a panel of celebrity judges). By contrast, world chess championships legislate increasing returns to winning (the defending champion advances automatically to the finals), and measure performance objectively (in a game of skill). In this way, variations in competitive parity have less to do with the local factors that generally preoccupy competitors (e.g., moving chess pieces, the charm or beauty of Miss America contestants),

Table 9. Domains of least parity: upper quartile z-scores

z-score	*n* = 53 industries(in bold)/domains	Leader
7.09	**Brewing (profit)**	**Anheuser-Busch (20)**
6.33	World Cup Baseball 1953–98	Cuba (17)
6.22	**Petroleum refining (profit)**	**Exxon (20)**
6.20	**Chemicals (profit)**	**Dupont (15)**
6.18	Olympic summer games medal count 1896–1984	USA (12)
6.00	**Pharmaceuticals (profit)**	**Merck (13)**
5.90	European Order of Merit rank (golf) 1971–90	Ballesteros (6)
5.88	**Scientific and photographic equipment (profit)**	**3M (12)**
5.86	**Soft drinks (profit)**	**Coca-Cola (20)**
5.86	**Soft drinks (ROS)**	**Coca-Cola (20)**
5.73	**Brewing (ROS)**	**Anheuser-Busch (17)**
5.73	World Chess Championship 1886–1952	Lasker (7)
5.70	Australian Women's Field Hockey Champion 1946–66	Western Australia (17)
5.70	World Snooker Championship 1965–85	Reardon (6)
5.67	**Computers (profit)**	**IBM (17)**
5.67	**Rubber and plastic products (profit)**	**Goodyear (15)**
5.64	**Foods (ROS)**	**Kellogg (9)**
5.60	NBA Most Valuable Player Award 1970–89	Abdul-Jabbar (6)
5.55	Wimbledon (tennis): women's singles title 1979–98	Navratilova (8)
5.40	Wimbledon (tennis): men's singles title 1979–98	Sampras (5)
5.37	**Publishing and printing (profit)**	**Gannett (13)**
5.27	**Brewing (ROE)**	**Anheuser-Busch (16)**
5.25	**Metal products (profit)**	**Gillette (14)**
5.25	Australian Amateur Billiards Championship 1935–60	Marshall (14)
5.20	**Forest and paper products (profit)**	**International Paper (8)**
5.20	U.S. Men's Handball Champion (singles) 1970–89	Alvarado (10)
5.14	Australian House of Representatives by majority party 1940–87	Labor (19)
5.11	**Apparel (profit)**	**Levi-Strauss (11)**
5.09	World Chess Championship 1955–98	Kasparov (7)
5.00	**Industrial and farm equipment (profit)**	**Caterpillar (10)**
5.00	PGA Tour money winnings (golf) 1960–79	Nicklaus (8)
4.91	U.S. Chess Championship 1960–79	Fischer (7)
4.88	Maltese Amateur Snooker Championship 1950–69	Borg (10)
4.82	**Foods (10-yr returns)**	**Tyson (8)**
4.78	U.S. NCAA lacrosse champion 1970–89	Johns Hopkins (8)
4.67	Davis Cup tennis 1969–88	USA (8)
4.67	MLB American League wins 1941–60	NY Yankees (14)
4.67	National Hockey League Stanley Cup 1954–73	Montreal Canadians (11)
4.60	NCAA Men's basketball champions 1970–89	UCLA (5)
4.43	**Soft drinks (ROE)**	**Coca-Cola (18)**
4.40	**Toys and sporting goods (ROE)**	**Mattel (12)**
4.40	Wimbledon (tennis): men's singles title 1959–78	Laver (4)
4.33	**Aerospace (profit)**	**Boeing (10)**
4.33	Davis Cup tennis 1949–68	Australia (15)
4.33	U.S. intercollegiate rowing champion 1950–69	Cornell (6)
4.27	Wimbledon (tennis): women's singles title 1959–78	King (6)
4.25	**Pharmaceuticals (ROS)**	**Merck, Amgen (6)**
4.18	**Foods (profit)**	**Sara Lee (5)**
4.13	National Basketball Association wins 1959–78	Boston Celtics (12)
4.11	National Basketball Association wins 1979–98	Chicago Bulls (6)
4.10	PGA Tour money winnings (golf) 1980–99	Norman, Strange (3)
4.00	**Metals (profit)**	**Alcoa (10)**
4.00	NCAA college football AP rank 1977–96	Miami (4)
5.13	**Mean**	**10.94/20**

Table 10. Domains of greatest parity: lower quartile z-scores

z-score	*n* = 53 industries (in bold)/domains	Leader
−5.12	**Scientific and photographic equipment (1-yr returns)**	**three firms (2)**
−5.12	**Metals (1-yr returns)**	**Maxxam (3)**
−3.11	**Aerospace (1-yr returns)**	**McDonnell-Douglas (3)**
−3.00	Men's U.S. Outdoor Speed Skating Championship 1970–89	Hamilton (4)
−2.80	**Forest and paper products (1-yr returns)**	**Sonoco (2)**
−2.56	Women's bridge champions (pairs): All-America Regionals 1948–70	Stein *et al*., Halloran *et al*. (2)
−2.40	U.S. Women's IBC bowling champion 1965–84	Morris (2)
−2.00	**Metal products (1-yr returns)**	**five firms (2)**
−1.63	**Mining and crude oil prod'n (ROS)**	**Burlington, Newmont (3)**
−1.56	**Textiles (1-yr returns)**	**West Point (4)**
−1.38	Indianapolis 500 champion 1956–75	Foyt (3)
−1.36	Men's British Amateur Golf Championship 1977–96	McEvoy (2)
−1.33	Australian clay target shooting champion 1948–67	Thomas (3)
−1.30	**Industrial and farm equipment (1-yr returns)**	**three firms (2)**
−1.29	**Soft drinks (1-yr returns)**	**Coca-Cola, Pepsico (10)**
−1.29	U.S. Presidential elections by party 1920–96	Democrat, Republican (10)
−1.29	Australian prime minister by party, ministries 38–57: 1968–99	Labor, Liberal (10)
−1.29	Australian Senate by majority party 1940–87	Labor, Liberal (10)
−1.25	**Mining and crude oil prod'n (1-yr returns)**	**Vulcan (4)**
−1.25	**Pharmaceuticals (1-yr returns)**	**three firms (2)**
−1.09	**Motor vehicles (ROE)**	**GM (8)**
−1.09	**Motor vehicles (1-yr returns)**	**GM (8)**
−1.00	British Women's Open Golf Championship 1976–96	Massey (2)
−0.88	Academy Award: best actor 1951–70	20 actors (1)
−0.78	**Apparel (1-yr returns)**	**three firms (2)**
−0.78	**Rubber and plastic products (1-yr returns)**	**Cooper, Mark IV (3)**
−0.67	Women's U.S. Outdoor Speed Skating Championship 1970–89	Merrifield (3)
−0.67	Women's bridge champions (pairs): U.S. Spring Nationals 1951–70	Wagar/Rhodes (4)
−0.63	**Metals (ROE)**	**Worthington, Wierton (3)**
−0.21	U.S. Senate majority party 67th–86th Congress: 1921–60	Democrat (11)
−0.18	Miss America 1980–99	three states (2)
−0.11	**Transportation equipment (profit)**	**Brunswick (6)**
−0.09	**Foods (1-yr returns)**	**three firms (2)**
0.00	American Bridge Assoc. Championships (open pairs): 1950–70	Pietri *et al*. (3)
0.11	Kentucky Derby winning jockey 1940–59	Arcaro (4)
0.11	Kentucky Derby winning jockey 1960–79	Hartack (4)
0.12	**Publishing and printing (1-yr returns)**	**Amer. Greetings, R&R (3)**
0.14	**Soft drinks (10-yr returns)**	**Coca-Cola (12)**
0.14	U.S. House of Reps majority party 67th-86th Congress: 1921–60	Democrat (12)
0.20	**Toys and sporting goods (1-yr returns)**	**Mattel (8)**
0.22	Women's World Figure Skating Championships 1970–89	Witt (4)
0.33	**Petroleum refining (1-yr returns)**	**Valero (3)**
0.38	Academy Award: best actor 1971–90	Hoffman (2)
0.44	**Transportation equipment (ROS)**	**Harley-Davidson (8)**
0.44	**Rubber and plastic products (ROE)**	**Rubbermaid, Gencorp (4)**
0.44	**Transportation equipment (ROE)**	**Harley-Davidson, Polaris (5)**
0.44	**Transportation equipment (1-yr returns)**	**Harley-Davidson (8)**
0.45	Pulitzer Prize national reporting 1965–84	four papers (2)
0.50	Sheffield Shield Australian cricket wins 1956–75	Victoria (8)
0.67	**Transportation equipment (10-yr returns)**	**Trinity, Brunswick (5)**
0.70	**Chemicals (1-yr returns)**	**Georgia Gulf (3)**
0.70	Australian Men's Amateur Golf Championship 1948–67	three players (2)
0.73	**Motor vehicles (ROS)**	**Chrysler (9)**
−0.82	**Mean**	**4.66/20**

than with domain-level welfare preferences and institutional engineering.

A natural parity theory would explain, for all competitive domains, what industrial organization explains in industry, namely the institutional rules and conditions that produce performance variance across domains. The dependent variable is the Gini coefficient (z-score), and the aim is to explain cross-domain variance using relatively few institutional features. A variety of methods could be used in empirical research, including econometric methods, case analyses, event studies (as in the baseball research), and experimental methods. Though we only suggest the barest essentials here, a natural parity theory would be of significant interest, providing a theoretical counterpoint to emerging complexity-based theories of self-organization, and suggesting important subsidiary linkages to the theory and practice of public policy and antitrust, and to theories of distributive and procedural justice.

Industry- and firm-specific advantage

Strategy research features an ongoing debate concerning the relative importance of industry, corporate and firm-specific sources of advantage (Hansen and Wernerfelt, 1989; Rumelt, 1991; McGahan and Porter, 1997). The data presented here emphasize intraindustry variance and do not enter directly into this debate, but they suggest the following connections. First, the Ginis and z-scores indicate the presence of firm-specific advantages, but when random processes and proportional growth heuristics are accounted for, intraindustry variance is reduced to a few extreme cases. Second, variance on cross-industry Ginis is surprisingly low (S.D. $=$ 0.12 on mean $= 0.60$), but larger across z-scores, and larger for some performance measures (profit, ROS) than others (10-year investor yields). In general, the data support a presumption of significant industry-based differences in competitive conditions (it was possible to take one interindustry Gini measurement, and this supported the presence of industry-level advantage—the z-scores were large, due chiefly to abnormal profit rates in pharmaceuticals: for ROS, the z-score was $+6.60$ (pharmaceuticals led all industries in 17 of the 20 years), and for ROE $+5.50$ (pharmaceuticals led 12 times)).

Though the current findings are consistent with interindustry and intraindustry variance, its emphases lay elsewhere, toward enabling strategy research to identify genuine outliers, whether they be firms, industries, or nonbusiness domains. Having said that, it is worth noting that the balance of the evidence in this study weighs more to the industry view than is common in recent strategy research. The Ginis show intraindustry variance, but this variance seems congenial to more concise explanations than those proposed in most theories of competitive advantage. By contrast, interindustry variance appears (as noted above) to justify a more wide-ranging, cross-domain performance theory than is currently available.

The art of overexplaining

If superior firm performance stemmed from the cultivation and protection of firm-specific competitive advantages, it would produce distributions abnormal under any parity model proposed in this paper. The data suggest that such distributions are rare, and confined mainly to performance measures with blatant serial correlation (see Table 9). As such, theories concerning long-term, firm-specific competitive advantages do not seem to have widespread application in industry. That such theories flourish reflects the predominance of stochastic parity as the null model—in comparison with the other models presented here, stochastic parity discriminates poorly between ordinary performers and outliers, and invites more explanation than the evidence requires.

If firm-specific competitive advantages exist, they are, in all likelihood, local and extreme phenomena, and highly resistant to useful generalization. The data do not prove that assertion, but they are consistent with it, and—in light of the rising dominance of firm-specific strategy theories—it is worth considering (see also Starbuck, 1992, 1993). Under alternative parity models, which enable comparisons with diverse scientific phenomena and nonbusiness competitive domains, the simple fact is that nothing unusual is happening in the performance of most industries. The action is in the extreme cases, and that is where strategy theories add their value. If they contribute to strategy research, the models proposed here do so by pointing the way to those outliers.

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APPENDIX

The Gini Coefficient

In Figure 1 (see text), the Gini coefficient is (Area A)/((Area A + Area B) − 20). Computationally, in domains with $n < 20$ competitors, the numerator and denominator are:

$$\text{Area } A = 10(n+1) - \sum_{i=1}^{n} \chi_i (n+1-i)$$

$$(\text{Area } A + \text{Area } B) - 20 = 10(n-1)$$

where:

n = number of competitors
i = competitors 1 through n, arrayed from last (fewest firsts) to first (most firsts)
χ_i = number of firsts for competitor i over the 20-year span.

In domains with $n \geq 20$ competitors, the numerator and denominator are:

$$\text{Area } A = 210 - \sum_{i=1}^{n} \chi_i (n+1-i)$$

$$(\text{Area A} + \text{Area B}) - 20 = 190$$