UCL CENTRE FOR ADVANCED SPATIAL ANALYSIS

UCL

WORKING PAPERS SERIES

Paper 112 - Jan 07

Visualizing Creative Destruction

ISSN 1467-1298

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Visualizing Creative Destruction

Michael Batty[1]

"The problem that is usually being visualized is how capitalism *administers* existing structures, whereas the relevant problem is how it *creates* them and *destroys* them."

Joseph A. Schumpeter (1938) **Capitalism, Socialism and Democracy**, page 84

Abstract

We introduce a series of methods for visualizing the dynamics of firm size as indicative of the way the creation of new economic entities destroy the existing order in the manner first sketched by Schumpeter (1938). We examine firm size distributions for every year from 1955 to 1994 for the top 100 firms listed in the Fortune 500. We show that although rank-size distributions from this data are remarkably stable, this masks a much more detailed microdynamics where firms are changing their size and rank in the prevailing order quite rapidly. These provide the signatures of creation and destruction and to visualize their form, we introduce the idea of half lives, rank clocks and distance statistics which reveal a cornucopia of dynamic behaviors. We first examine changes in firm size measured by revenue earnings and then we contrast this with profits per earnings data which reveals another picture of these processes of creation and destruction.

Preamble

'Creative destruction' is the term coined by Joseph Schumpeter (1938) to describe the way in which economic activities, specifically firms or companies, evolve and co-evolve through competition and innovation. Capitalism, argued Schumpeter, is not only efficient in that it enables

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more productive to displace less productive firms but it is simultaneously both creative and destructive. Existing firms find it virtually impossible to create an environment in which they are able to spontaneously generate and implement sufficiently deep-rooted innovations to stay ahead of the market (Foster and Kaplan, 2001). Schumpeter, in fact, argued that such innovation could be so rapid that it would eventually destroy the entire system through its hostility to the existing social order. But in the 70 years since his work was first published, successive waves of innovation and the demise of great companies by upstarts does not seem to have overwhelmed the system's ability to adapt and mutate, to evolve new forms of industrial organization which are hostile only to an established order which is in constant transition anyway.

The purpose of this short paper is not to question Schumpeter but to grasp synthetically what the dynamics of creation and destruction mean to modern economies. One way of exploring how we might visualize such a dynamics is by showing how firm sizes change over long periods of time. There is in fact a substantial literature on the distribution of firm sizes in modern economies, and even in Schumpeter's time, there was recognition that the distribution of firm sizes was remarkably regular regardless of where and when such distributions were observed (Gibrat, 1931). Such regularities in firm size-distributions are best seen as power laws which are the stuff of 'social physics'. In essence, if you examine the size of firms according to the frequency of their occurrence, patterns are revealed where there are many more small firms compared to large firms with the relationship a consistent inverse between frequency and size (Sutton, 1997). To provide an idea of this relationship, we plot the reported revenue earnings of the top 100 firms in the **Fortune 500** for 1955, when the current series began[2], against their rank which we show in Figure 1 as a log-log plot. To establish the fact that this kind of regularity 'appears

[2] Fortune 500 data from 1955 to 2005 is available for each year from the CNN Money web site http://www.money.cnn.com/. We only use the data from 1955 to 1994 because the series appears to have been redefined in 1995.

stable' through time, we also plot equivalent data two generations (40 years) later for 1994 which we also show in Figure 1.

On looking at the stylized facts that compose this data, a naive observer with no knowledge of the modern economy might be forgiven for thinking that these relationships show that little has changed in the US economy over a 40 year period. The curves appear to be the same, simply displaced in time, with standard statistical analysis of their aggregate form failing to reveal any dramatic differences. But nothing could be further from the truth. From the 100 firms making up the list in 1955, 39 (percent) remain in 1994, and if the changes in each year from 1955 are examined, this reveals a more dramatic micro-dynamics with firms entering and leaving the list with great rapidity. By 2005 in fact, only 17 firms are left from 1955 but there are limits to this data because of the massive redefinition of firms in the dot.com era through mergers and acquisitions. This reinforces the notion that the US economy is remarkably volatile with respect to its dominant firms but within an aggregate envelope that suggests an intrinsic order reflecting a balance of ceaseless competition and innovation. There is little doubt that the process whereby this volatility in micro-dynamics is consistent with a very stable macro-dynamics remains a puzzle. But it is also reveals that those processes of creation and destruction referred to by Schumpeter need to be extracted from these aggregate data. It is the purpose of this short paper to propose ways in which this might be done.

The Distribution of Firm Sizes

Phenomena based on sets of like objects or entities in many fields whose size changes over time through competition, evolution or more complex processes such as co-evolution display an ordering based on their size whereby the largest objects are much less frequent than the smallest. In human systems, the competitive processes which drive the changes which lead to such as ordering involve acquisition of wealth, reputation, economies of scale and so on although models that attempt to explain the inequalities that result from such processes are often based on random but proportionate growth which favors entities that are already large. There are a number of mathematical models based on growth theory which are consistent with the kinds of distributions that we focus on (Lucas, 1978, Aghion and Howitt, 1992). Our purpose here however is not to explore such mechanisms but to simply track the changes that can be observed which are usually consistent with one or more of these hypotheses.

In terms of firm size, Gibrat's (1931) early work suggested that typical size distributions follow a skewed distribution which he argued was the lognormal where the proportionate growth processes that he and others have proposed (see also Steindl, 1965; Ijiri and Simon, 1977) are entirely consistent with the generation of a lognormal. There is however still considerable doubt about this (Axtell, 2001) largely due to the ambiguity over definitions of firms themselves as well as the size attributes that might best characterize them. In any case, the portion of the lognormal in which the largest and perhaps the most significant firms lie can be very readily approximated by a power function with attractive attributes of scaling which imply consistent externalities within the economy.

There is quite a strong disconnect between research into the statistics of firm size and more qualitative studies of firm dynamics which in some respects marks a difference between aggregate and disaggregate approaches (Sutton, 1997). We will briefly review the statistical theory as this is a prerequisite to our work on micro-dynamics and we thus begin with the standard form of the power law. Defining the frequency $p(x)$ with which a firm of size x occurs (where frequency is represented as a probability density), then this density is

$$p(x) = Zx^{-\alpha} \qquad (1)$$

where Z is a scaling constant and α is a parameter that controls the concentration of the distribution. As α increases, then the range of firm sizes, hence by implication their concentration, decreases. The form that we work with here is the counter-cumulative function $P(x)$ that is derived by integrating (1) from some value x to its limit ∞. Then

$$P(x) = \int_x^\infty p(x)dx \sim x^{-\alpha+1} \quad . \qquad (2)$$

From (2), it is straightforward to derive the scaling constant Z which is determined from the normalization of the probability density to $P(x) = 1$. To perform this, a minimum value of $x = x_{\min}$ must be set as the function diverges when firm size is zero but for practical purposes, such a lower bound is quite acceptable and indeed necessary for empirical work with the discretized version of this function.

The counter-cumulative can also be interpreted as the rank $r(x)$ of the firm in its distribution. As frequency is proportional to density, a firm size x_1 can be found from (2) which ensures that $r(x_1) = 1 = F(x_1) \sim P(x_1)$. The same can be determined for the next firm size which is $r(x_2) = 2$ and so on with this relation being written simply as

$$r(x) \sim x^{-\alpha+1} \quad . \qquad (3)$$

In its inverse form where size is proportional to rank, (3) becomes

$$x \sim r(x)^{-\frac{1}{1-\alpha}} \sim r(x)^{-\beta} \quad . \qquad (4)$$

β is now the parameter of this distribution and this clearly varies inversely with α, the parameter of the density function; as β increases, the slope of the rank-size curve traced out in (4) falls, implying greater dispersion of firm sizes across their distribution.

Equation (4) is the relationship that we show here. We have already plotted the log transform of this in Figure 1 which is called a 'Zipf plot' after Zipf (1949) who used this graphic in his work on city sizes and the distribution of words. In fact, practice varies between estimating (3) or (4), largely, it seems, as a matter of taste. For some density distributions, it has been hypothesized and occasionally demonstrated across a variety of fields that have invoked this scaling distribution, that $\alpha = 2$ and $\beta = 1$. This implies that the rank-size in (4) is a rectangular hyperbole although such a 'pure' form of relationship is currently regarded as 'accidental', notwithstanding arguments that suggest such relations may emerge in systems that are homogeneous with few market imperfections and 'free trade' between the entities (Gabaix, 1999). The point here however is that values of $\alpha < 2$ can be mathematically tricky with respect to defining the mean value of the density although as long as $\alpha > 1$, no difficulties are encountered with discrete distributions (see Newman, 2005).

We are now in a position to show how regular the distributions of the top 100 firms are at each yearly interval from 1955 to 1994 using the Fortune 500 data which we illustrated earlier. In Figure 2, we plot all 40 of these distributions by transforming the data logarithmically; that is we plot the log of size $\ln(x_i)$ against the log of rank $\ln(r_i)$ where i is the firm in question. This implies that we are transforming equation (4) to

$$\ln(x_i) = K - \beta \ln[r(x_i)] + \varepsilon_i \tag{5}$$

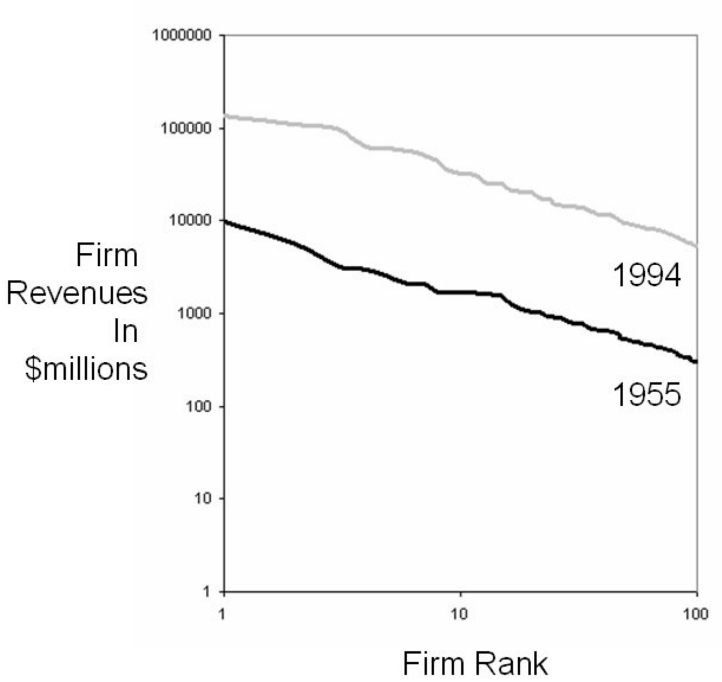


Figure 1: Firm Revenue v Rank: 1955 and 1994 from the Fortune 100

Log-log regression of revenue against rank yields slope coefficients β (& r^2 correlations) of -0.723 (r^2=0.992) and -0.760 (r^2=0.993) for 1955 and 1994 respectively. The less biased maximum likelihood method yield equivalent slopes of -0.697 and -0.691 for 1955 and 1994 using Hill's bootstrap estimator as described in Newman (2005).

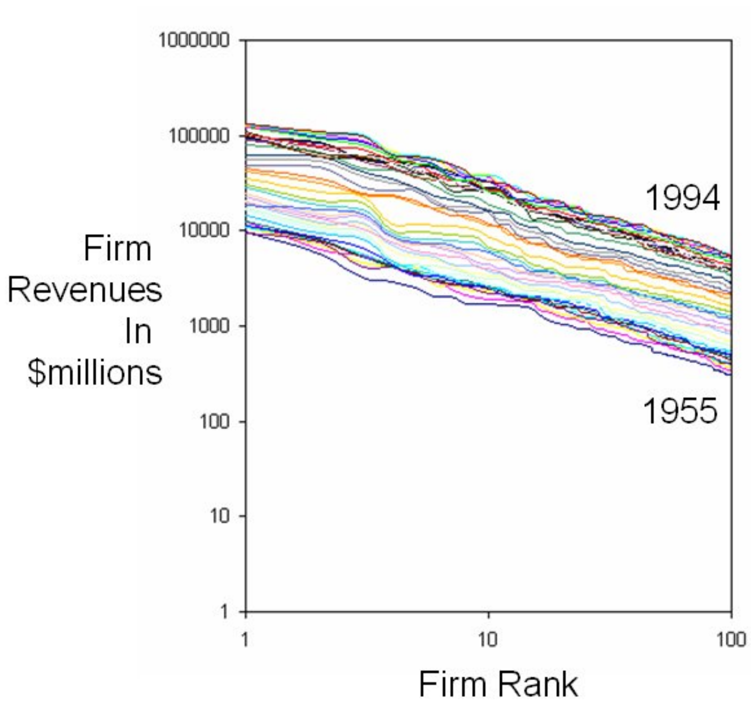


Figure 2: Firm Revenue v Rank: 1955 - 1994

where K is the log of the scaling constant associated with (4) and ε_i is an error term. Equation (5) is linear and this suggests standard methods for estimating K and β, hence α. However before we illustrate this, it is important to stress that these aggregate pictures hide any clear variations in individual firm sizes during the period in question. In short it is impossible to detect any of the volatility posed by mergers and acquisitions, changing market share and any other changing attributes of the firms that make up these distributions. All we are able to detect are slight shifts in the lines which we 'speculate' as being due to market conditions such as the 1973 Oil Crisis and the early 1990s recession.

To make this completely clear, we have estimated β for each time period, regressing size $\ln(x_i)$ against rank $\ln(r_i)$ from which we have computed α as $1+(1/\beta)$ and we plot these in Figure 3. Despite the fact that the r^2 correlations between $\ln(x_i)$ and $\ln(r_i)$ exceed 0.981 for all 40 years, this is not a particularly robust estimator although it has been widely used. Thus we have also used the Hill estimator, stated by Newman (2005) amongst others, as

$$\alpha = 1 + \left(n \Big/ \sum_{i=x_{\min}}^{x_{\max}} \ln \frac{x_i}{x_{\min}} \right) \quad . \tag{6}$$

We have also plotted α from (6) and its β equivalent value $1/(\alpha-1)$ in Figure 3 and it is immediately clear that the values are fairly consistent with one another. α has a mean value over the 40 years of 2.301 using (6) in contrast to $\alpha' = 2.314$ using the indirect derivation from (5). β has a mean of 0.713 from (5) compared to its indirect derivation $\beta' = 0.723$ from (6) and as Figure 3 implies the variances of these values are quite small. The most important point however is the comparative lack of variation in these slope parameters, although concentration seems to decrease through the 1960s, reversing about the time of the Oil Crisis and then bumping along without dramatic changes until the mid 1990s when our data ends and the boom-bust cycle of the dot.com era begins. There is not much else that can be said from such aggregate data and thus we must now inquire as to how we might visualize the massive changes that do actually occur in these distributions during this comparatively 'quiet' period.

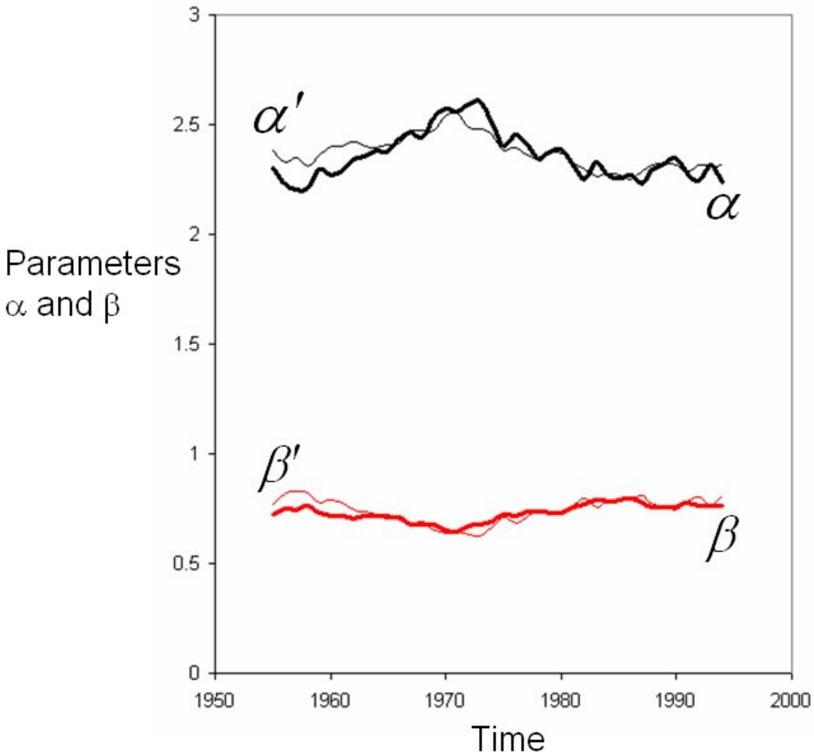


Figure 3: Changes in the Density and Rank-Size Parameters α and β

Firm Dynamics: Shifts in Rank and Size

Before we launch into an analysis of the Fortune 100 firm-size distributions, we should inject a word of caution. It is quite clear that firms, like cities and many objects in the social world, are hard to define unambiguously. More theoretical expositions focus on the 'basic business unit' which avoids the empirical problems of defining objects that are ambiguous in their function and scope as are firms and related conglomerates (Metcalfe, 1998). But we have no such luxury here as we have to deal with data whose reporting unit is the institution of the firm. The Fortune list does include several firms that combine during the period in question which is equivalent to the merging of suburbs and central cities in the analysis of city-size distributions (Batty, 2006), and we have not made any effort to refine the data set to account for these. This is largely because we view our ideas about visualization of firm dynamics as a preliminary foray and in future work, we will identify and use data sets that are more consistent. It is in this sense that we refer to the data as 'stylized facts'.

To illustrate the changes that are hidden in these distributions, we first need to introduce some additional notation which helps clarify differences that occur over time within the data. We will work with revenue of each firm observed at time t as a measure of its size which we call p_{it} where i is the firm whose rank order is r_{it}. Thus the firm i at position r_{it+1} is not necessarily the same firm as that at time t which is r_{it}. However to compare shifts in the rank of this firm, we need to compare its position r_{it} with its new position r_{jt+1}, and thus we must keep track of how firms change their rank order through time. If the firms are ordered by name from $k = 1, 2, ..., \ell, ..., m$, then for each rank order and time we define $m_{it} = \ell$ where ℓ is the given firm from the list.

Actual revenue changes at each rank order are not significant as we have already shown that the rank-size curves in the Zipf plots in Figures 1 and 2 are very close. In fact if we were to plot these curves using the normalized revenues which we calculate as $p_{it} = P_{it} \Big/ \sum_j P_{jt}$ where P_{it} is the observed revenue of firm i at time t, then the curves would collapse onto one another. To show this another way, we can compute the average proportional differences in the revenue at each rank order between any two years t and τ as

$$\Pi_{t\tau} = \sum_i \frac{|p_{it} - p_{i\tau}|/p_{i\tau}}{n} \qquad , \tag{7}$$

where n is the number of common firms in the list at those times. The percentage of revenue that is common to any two years is thus

$$\pi_{t\tau} = 100\,(1 - \Pi_{t\tau}) \qquad , \tag{8}$$

and the average percentage over the entire period is thus

$$\pi = \sum_t \sum_\tau \frac{\pi_{t\tau}}{T(T-1)} \quad , \quad t \neq \tau \, , \tag{9}$$

where T is the total number of years over which the shifts can be calculated from observed data. We plot the percentage of revenue common to any two years in Figure 4(a) where it is very clear that there is no variation in this over time and that on average almost 92 percent of revenue is the same from any year to any other. This simply confirms what the regressions illustrated above show, that there is remarkable constancy in the percentage revenue that the top 100 firms control, regardless of what those firms are and at what time they exist in the top 100. There appears to have been a mild tendency for this percentage to fall in the early 1970s but in general the average value hovers around π.

To show the real change, we must examine what firms remain in the top 100 during this time and our first and simplest measure is to simply count the firms that are common to any two years in the 40 year time series. As we are dealing with 100 firms at each period, then this number is also the percentage of ranks that are common. There is no simple formula but an algorithm is easy to define to count the number of firms that are common to this top 100 at time t and at time τ. Then if $m_{it} = \ell$ and $m_{j\tau} = \ell$, $\forall_i, \forall_j$, we count z common firms over all the lists and thus the number (and percentage) is

$$\rho_{t\tau} = z \qquad . \tag{10}$$

We can also count the total number over all time differences and compute the average as

$$\rho = \sum_t \sum_\tau \frac{\rho_{t\tau}}{T(T-1)} \quad , \quad t \neq \tau \qquad . \tag{11}$$

This average is about 70 percent. If we examine the 1955 data at the start of the series, the number of firms remaining in the list in 1994 is 39 while if we take the mid year in the series (1974), then the number of firms that are common to 1955 in this year's list is 62 while only 60 still exist in 1994. The plots shown in Figure 4(b) reveal patterns of quite regular entry and exit from the top 100 for all periods from which we can compute the half life – the average number of years in which half the firms in the list at any given year remain – as 28 years. These curves appear linear in time and on a somewhat speculative note, we have fit a linear model to the 1955-1994 curve (the red plot in Figure 4(a)) from which we are able to estimate the number of years to the time when no firms from the original list remain as 65 years. Thus by 2020, we might expect that no firms from the 1955 list will remain in the top 100.

To explore the dynamics of individual firms that make up the substantial changes in rank, we could plot the shifts in rank in the Zipf plots which make up the rank-size space in Figures 1 and 2. Instead of connecting the points defining the rank order for a particular time, we connect the points for each firm as its rank and size changes through time. If the ranks never change (but assuming the sizes change because revenues grow), then this plot would reveal vertical lines for each firm in the rank-size space. What we do is color the firm according to what rank and at what time it appears in the series from 1955 to 1994 on a spectrum from red to yellow to green to blue. For example the firm ranked number 1 in 1955 is colored red while the firm ranked 100 in 1994 is colored blue. Each firm is colored on the spectrum between these limits according to its rank when it enters the series. We show this picture of the rank-space in Figure 5 from which the age structure of the firm-size distributions is obvious. What is less obvious is that the firms at the very top are better established and change less than the lower ranked firms while there are significant winners and losers in terms of rank for which the most dramatic changes can be picked out on the graph. But in general, this graphic gives much less significance to time than to size and rank and thus we have introduced a new visualization called a rank clock which makes no reference to size, and is consequently much clearer (Batty, 2006).

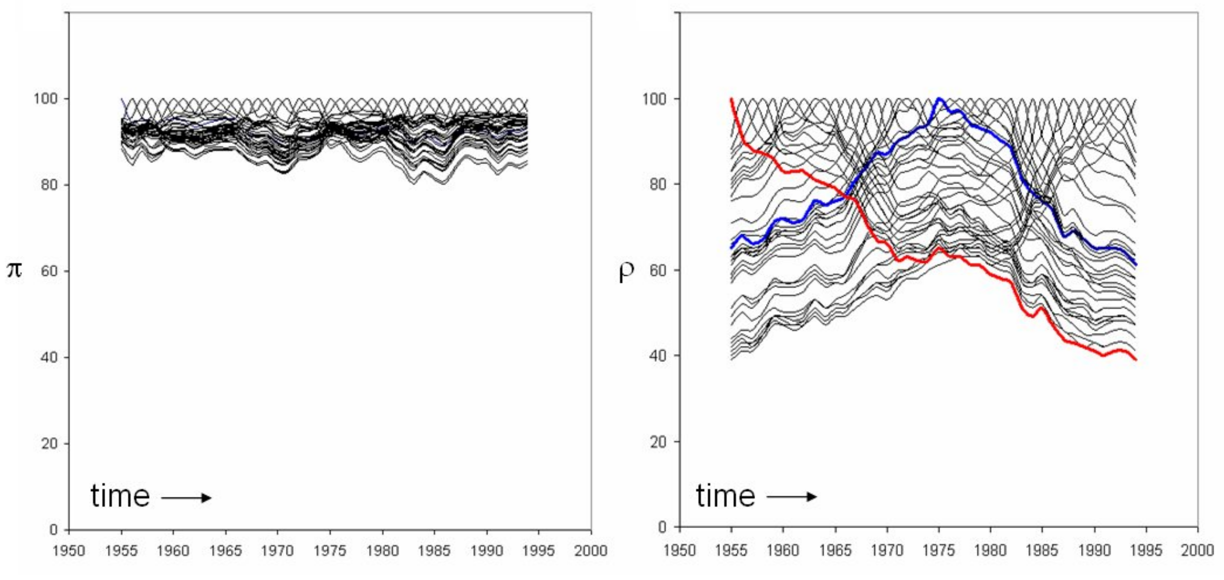


Figure 4: Percentage Shifts in Firm Size a) Revenues and b) Rank Orders

The percentage shift in revenues compares a firm's revenue normalized by overall size at the year in question with the firm at the <u>same rank</u> at each point in time before and/or after the given year (a). The percentage shift in rank compares the <u>same firm</u> at each year before and/or after the year in question (b). The curve in red in (b) indicates firms disappear from the top one hundred ranks through time, while the curve in blue shows the same but both before and after the middle year in the series 1974-5.

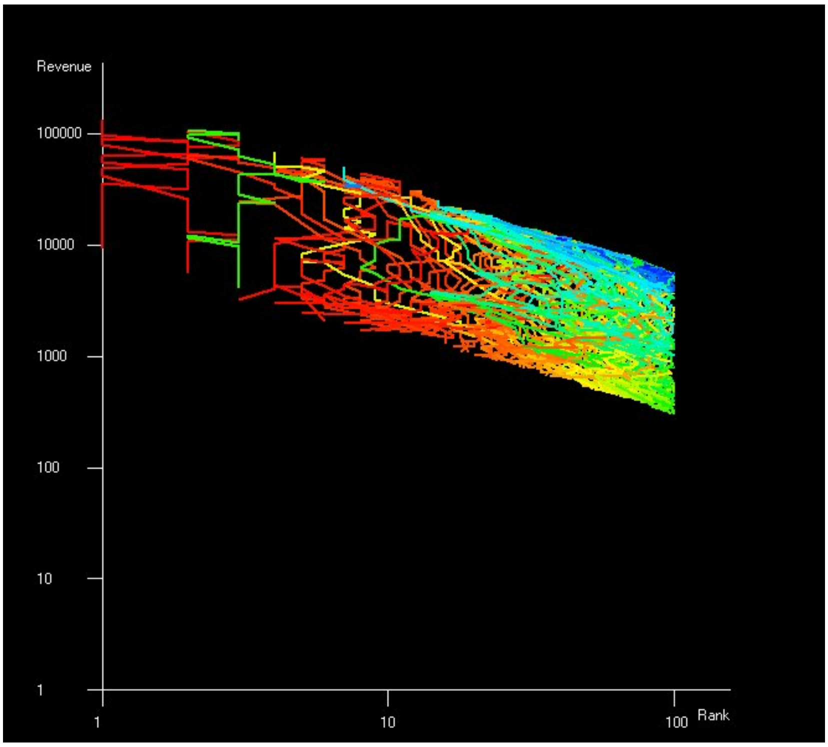


Figure 5: Changing Ranks in the Rank-Size Space

The colors indicate the time and rank at which the firm enters the top 100, with the first ranked, first time firm being red, then to yellow, green and the last ranked, last time firm being blue.

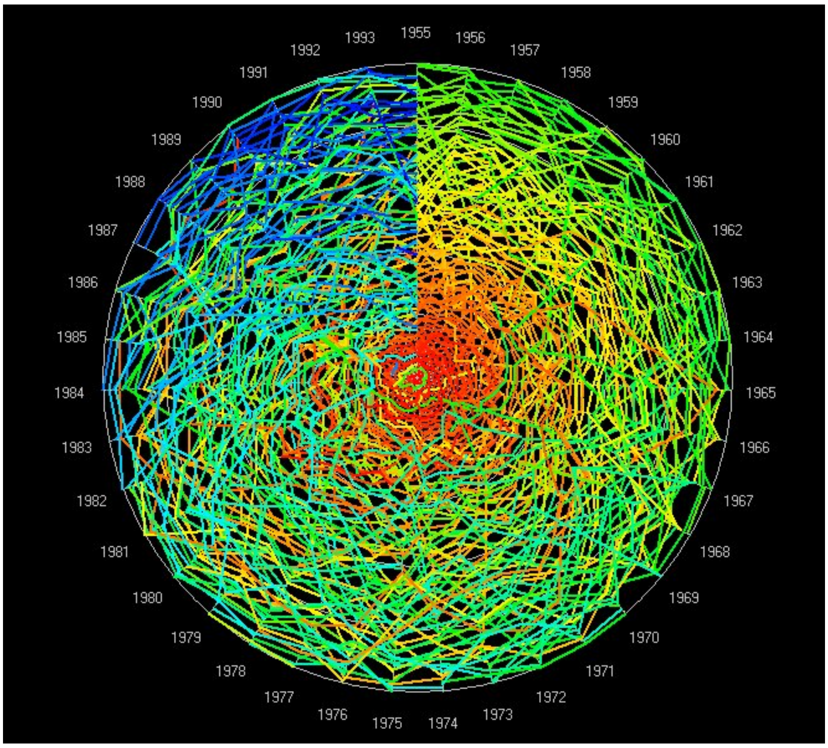


Figure 6: The Rank Clock for the Top 100 Fortune 500 Firms 1955-1994

The rank clock matches the temporal dimension to the 24 hour clock where the ranks at each time are positioned on the axes associated with the time in question. The centre of the clock is rank 1 while the edge or circumference is rank 100. If a firm remains at rank 1 throughout the time series, it is plotted at the centre, whereas a firm which is always rank 100 marks out a circle around the circumference of the clock. Firms that gain in rank as time proceeds mark out a spiral from the edge of the clock to the centre while firms that decline in rank spiral out from the centre to the edge. This suggest that there may be ways to characterize the behaviors of each firm and classes of firms from the clock but first we will look at the aggregate pattern revealed when all firms are plotted in this way. Using the same color scheme as for the rank-space in Figure 5, the clock is shown in Figure 6 from which one can trace the firms that rise and fall in the space much more clearly. In fact each individual firm can be plotted separately and we will do this in a moment.

However, the clock itself suggests several aggregate properties of the data set. The entry of new firms is clearly seen in the plot as the color balance changes. Moreover the relative volatilities of ranks is shown by the fact that the entire picture is one of spirals of different kinds as well as oscillating circles while some firms enter and exit several times during the 40 year period. There is a lot of work still to be done using clocks in comparative sense, examining their overall morphology as signatures of how different systems behave and this might be done in terms of their shape, their color balance and so on. But to proceed, we first need overall measures of shift which pick out the key events which determine this microdynamics.

A good measure of change which goes beyond counting the number of firms that that enter or leave the top 100 each time period is to compute the change in ranks of relevant firms from year to year and to produce some aggregate statistic of this change. However, we underestimate this change in our current analysis because the rank of a firm before it enters the top 100 is not known, nor is it once it leaves. Thus these shifts are not counted. We could get better estimates if we did the analysis for the top 100 firms with data from the top 500, say but we have not attempted this yet. Defining the rank change d_{it} for a firm i between time t and $t-1$ as

$$d_{it} = \left| r_{it} - r_{jt-1} \right| \qquad \text{where } m_{it} = m_{jt-1} = \ell \ , \tag{12}$$

the set of common firms that are part of this comparison between time $t-1$ and t is called Ω_t of which there N_t firms. The distance in (12) can be plotted directly in clock form as a vector between $t-1$ and t but an average measure of distance or rank-shift for each time period can be computed as

$$d_t = \sum_{i,j \in \Omega_t} \frac{\left| r_{it} - r_{jt-1} \right|}{N_t} \quad . \tag{13}$$

An overall measure of shift for the particular system, in this case the top 100 firms from 1955 to 1994, can be defined by summing the rank-shift averages over all time periods as

$$d = \sum_{t=1}^{T} \frac{d_t}{T} \quad , \tag{14}$$

where T is the total number of years of the data. These statistics mean that we can compare different systems in different places as well as at different times and they provide some measure of the volatility of change. We plot the distance clock based on $\{d_{it}\}$ for all relevant firms in Figure 7 and it clear from this that the earliest and top ranked firms do not change as much as the newer and lower ranked entries. There are occasional spikes of activity as individual firms shoot to the top or leave the list but the average d_t is fairly uniform varying from a low average change of 3.397 ranks each year to a maximum of 7.988 with an overall average d of 5.158. The maximum rank shift of any firm in any year throughout the 40 years is 50 while the minimum in several cases is 0, no shift. In Figure 7, we set the maximum axis as 50 and we also show the average for each time period by the thick white line.

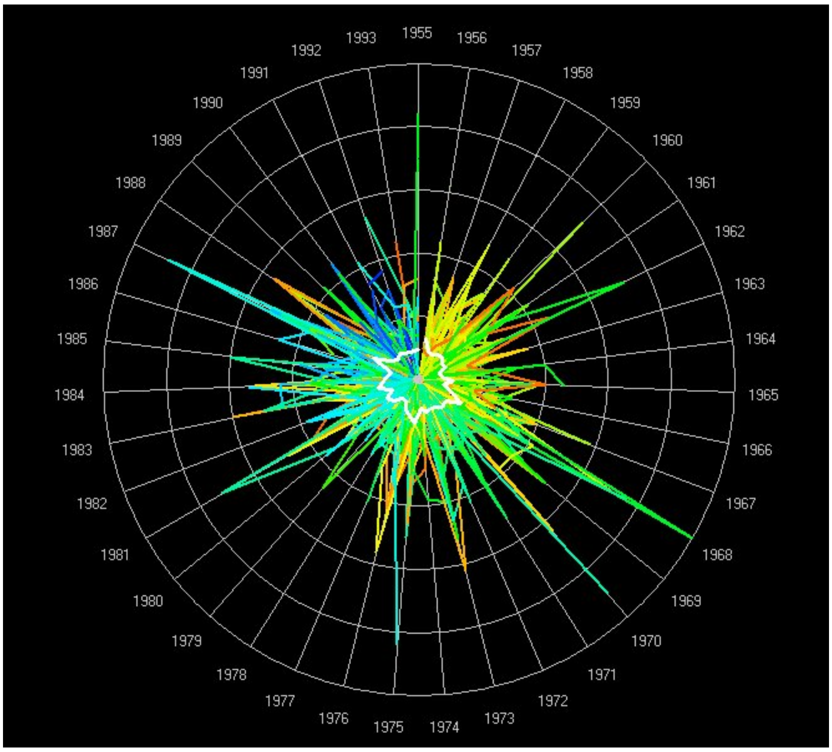


Figure 7: The Distance Clock Illustrating Rank Shift

The Micro–Dynamics of Individual Firms

The overall signatures revealed by the patterns and morphologies of the rank and distance clocks can be easily unpacked with respect to individual firms. In Figure 8, we choose 7 firms, all of which are present in at least 20 of the 40 years, and which show typical behavior. Firms that grow or decline in the same direction – into the clock if they are gaining in rank and out if they are losing rank – are indicated by slow or fast moving spirals. In fact, rank shift is a measure of velocity in the system, overall as in the averages d and d_t or individually in d_{it}. Firms that retain their rank within normal limits are shown as circular trajectories on the clock. Of course many firms only approximate these patterns and several in the series both gain and lose rank during the period. In this particular data set, we have not accounted for mergers and acquisitions and thus the picture we present is quite stylized as we implied earlier.

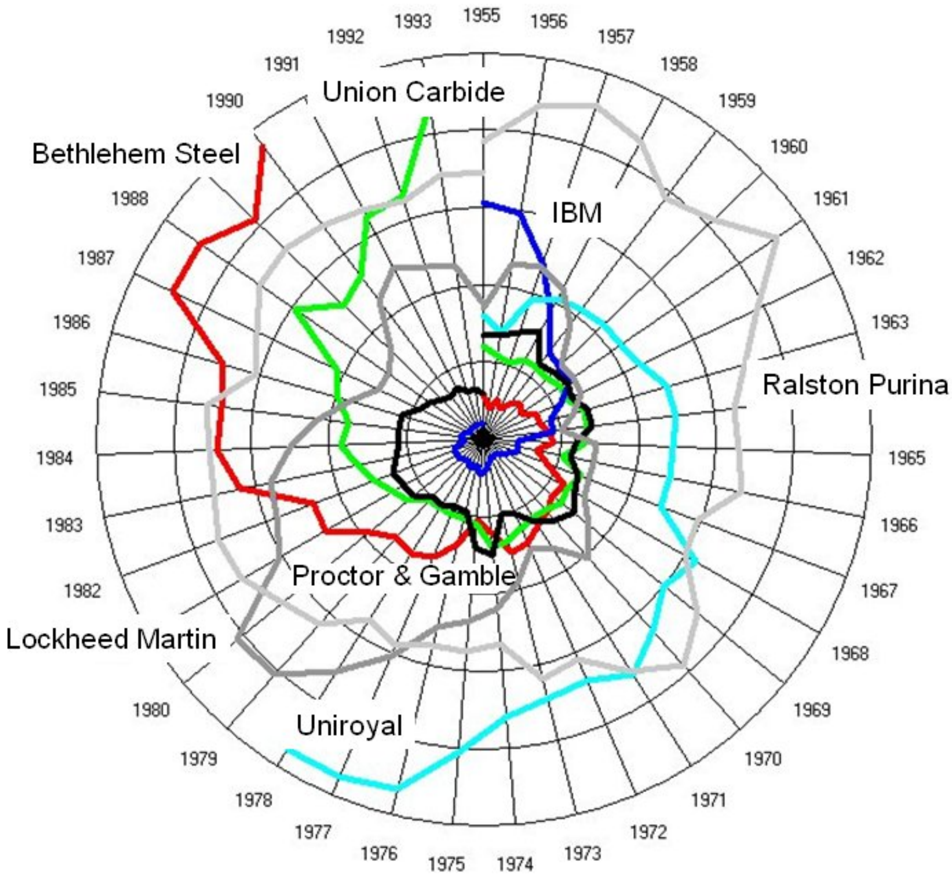


Figure 8: Key Trajectories of Firms

This clock shows the key trajectories which indicate growth – inward spirals (IBM, Proctor and Gamble), decline – outward spirals (Bethlehem Steel, Union Carbide, Uniroyal), and relatively constancy (Lockheed Martin, Ralston Purina)

In many ways, these visualizations only come into their own as ongoing and routine analysis tools when users can key in a firm and watch its behavior relative to the overall system or to other sets of firms. Hence there are many applications that spin off from this kind of use. Here all we will illustrate is one way forward. We can group firms into industry types and examine their behavior and casual observation of the data reveals that different sectors have behaved somewhat differently during this period. Here we will define three sectors and examine these in terms of the biggest firms based on rubber and steel, automobiles, and computer technologies. What we might anticipate is that during this period rubber and steel would have declined for this era marks the end of the industrial period and the very early years of the postindustrial. Firms in this sector have declined as the industry has gone offshore. The automobile industry has remained in a somewhat steady state despite the Japanese threat in the 1980s and we might expect some degree of constancy in terms of rank here. Lastly computer technologies are mainly dominated by hardware during this period. The shakeout associated with the drift to software and to routine manufacture only really began in the early 1990s and there is little evidence of any decline in computer based firms from this aspect of the data set. Indeed quite the opposite has happened as we show below.

In Figure 9(a), we show the individual trajectories for a sample of firms involving rubber and steel, in 9(b) firms in the automobile industry and in 9(c) computer technology firms. Of the sample rubber and steel companies we have chosen, all exist in the top 100 in 1955 but five of these disappear by 1994 and the one remaining, Goodyear Tire and Rubber also loses rank. In contrast for the four automobile firms, the big three – Ford, GM and Chrysler – stay at the top with no sign that they are losing their preeminence. American Motors has a patchy performance in and out of the top 100 until it was acquired by Chrysler in 1987. The computer technology firms all gain rank. IBM is the classic in that it moves rapidly to the top from 1955 whereas Digital, Motorola, and Texas Instruments all zoom towards the top ranks from their entry in the 1980s. CDC briefly enters the top 100 but its collapse and subsequent disappearance is a portent of future troubles for manufacturing mainframe and minicomputer companies which occur at the end our series just before the dot-com boom begins.

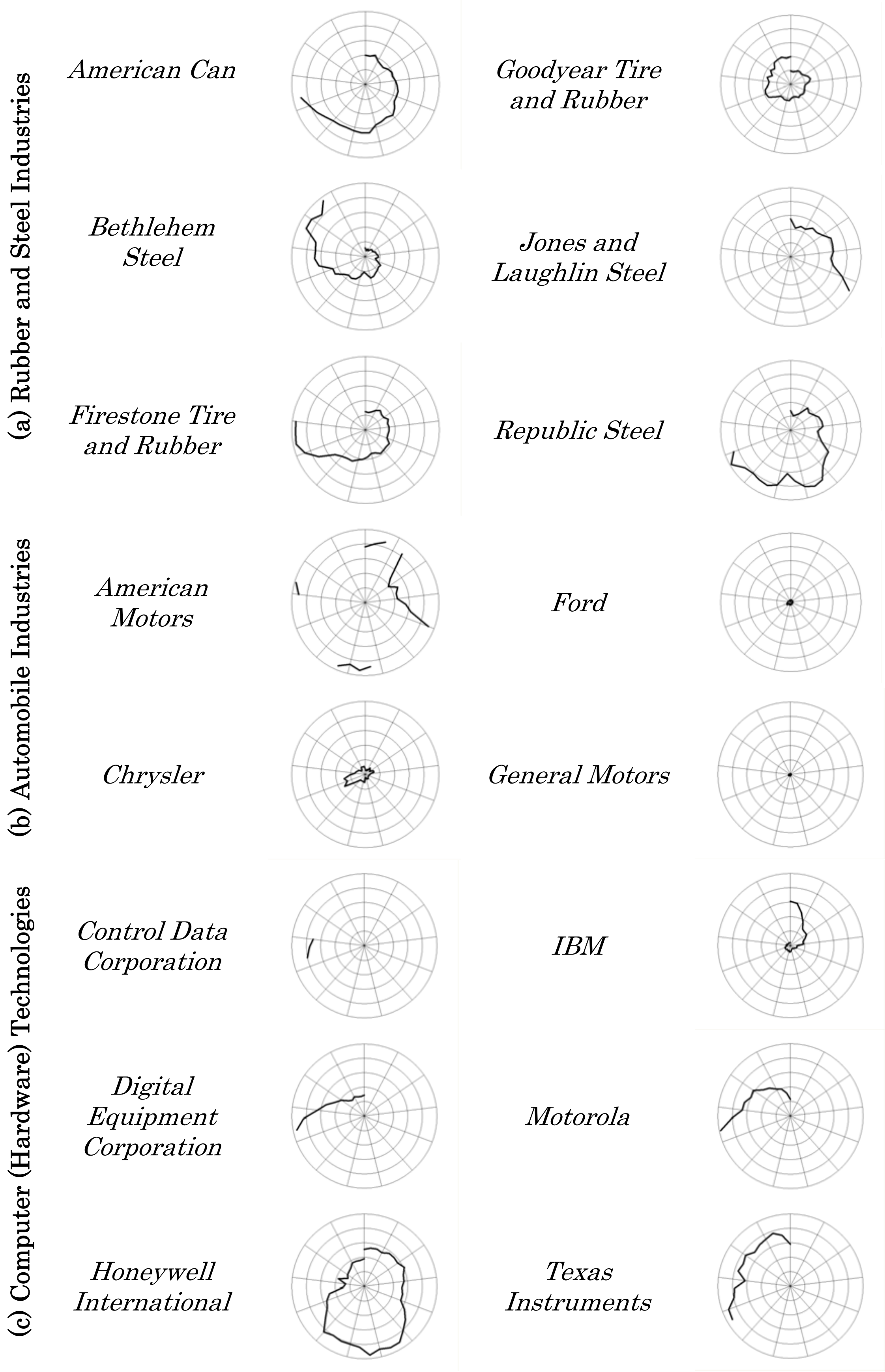
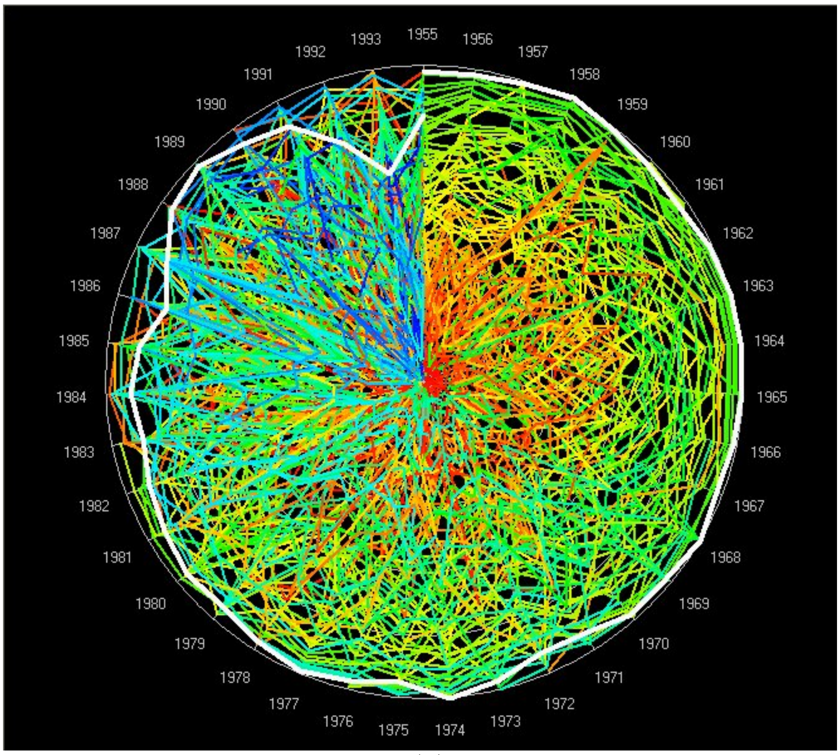


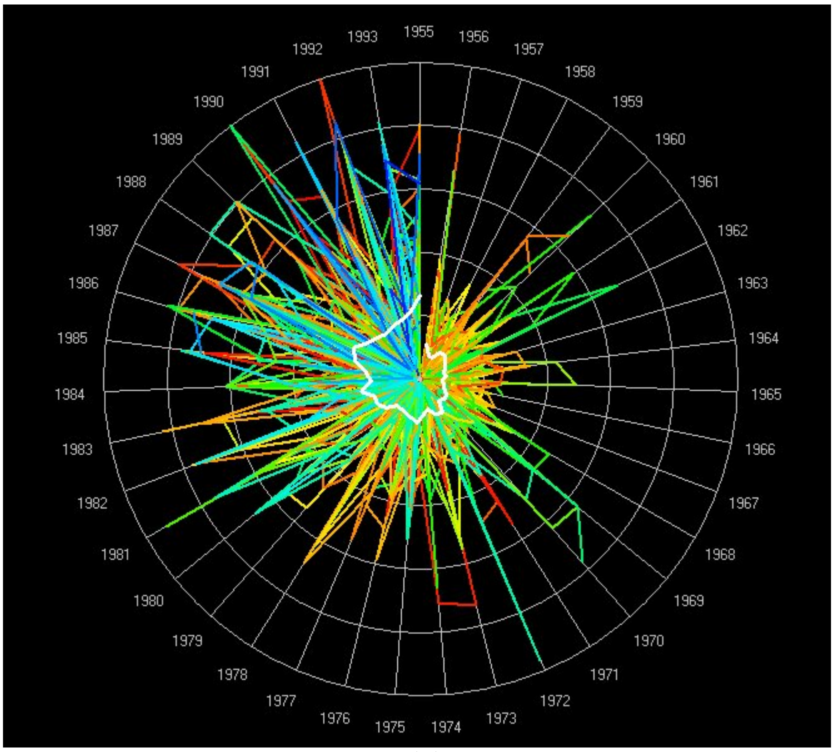
Figure 9: Individual Rank Trajectories for Clusters of Firm by Industry/Sector

So far we have measured the size of firms using their earnings or revenues. We assume that as revenues grow, this shows that the firm is increasing its dominance in the market in contrast to decline when they are loosing market share. We hypothesize that the usual pattern is a growth in revenues when a firm is being created and a fall when it is being destroyed. But the picture is much more complicated because revenues show dominance not performance and we might expect that creation and destruction would imply respectively increased and decreased performance of the firm. A simple measure of performance is profit and when we normalize this in terms of profits per earnings (profits/revenues), this gives an index that we assume will vary with growth and decline. As firms grow in their creative stage, this ratio increases; as they reach maturity this stagnates and when they decline, the ratio falls and often the firm becomes unprofitable (Foster and Kaplan, 2001).

The Fortune 100 data includes this index as well as other measures of size that we have not yet used such as employment from which another measure of performance – productivity – might be derived. In Figure 10(a), we plot the rank clock for the profits/earnings ratio where we also show by the thick white line the rank at which the firms in the top 100 become unprofitable i.e. where their profits become losses. It is immediately clear that the periods when firms experience most losses is in the early 1970s, the mid 1980s and then at the very end of the series in the early 1990s. These coincide with the relatively mild recessions in the US economy and the end of the cold war. The rank clock shows much greater volatility in fact in terms of profits/earnings movements than that involving revenues (in Figure 6) with some very large shifts in rank that are formally examined in terms of the distance measures in the distance clock which we show in Figure 10(b). Here the maximum rank shift is 83 compared to 50 for the clock measuring the distances for revenues in Figure 7.



(a)

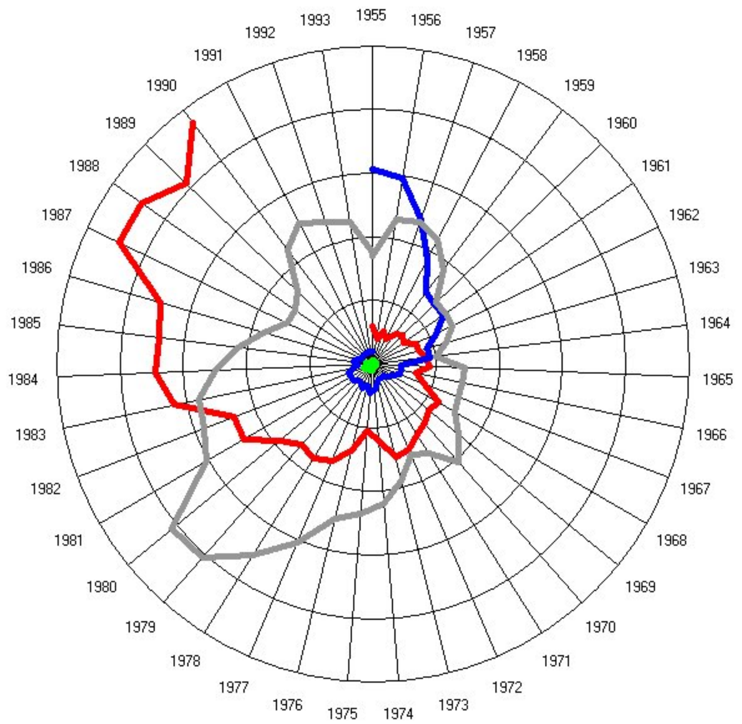


(b)

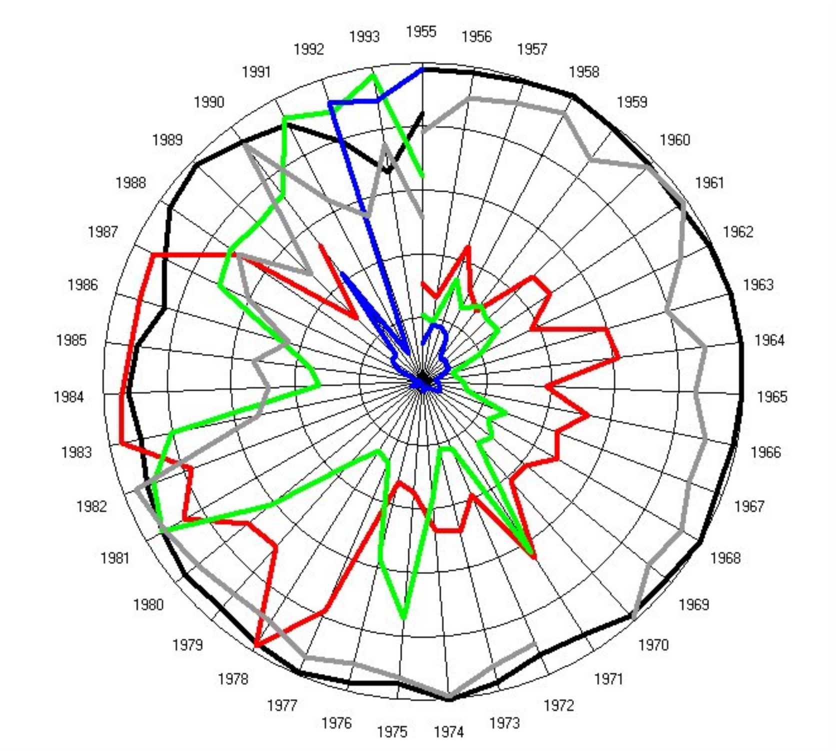
Figure 10: (a) Rank and (b) Distance Clocks for Profits-Earnings Ratio of the Fortune 100 Firms

The picture is made even more complicated when we examine each firm with respect to its trajectories of revenue and profit ratio change. To provide a sample of this kind of analysis, we choose four firms which from our previous analysis seems to reveal typically different behavior in the rank clock space with respect to change during this 40 year period. We choose Bethlehem Steel as an example of spiraling decline in revenues indicative of a firm being destroyed, General Motors as a firm that retains its rank as number 1 or 2 at the top of the US economy with its continuing stranglehold on the US consumer market, IBM as an example of spiraling growth with the company moving through its creative and maturing phases during this period; and Lockheed Martin, an aerospace company which has held its own during this period as it has adapted to changes in aircraft/space technologies and in defense contracting.

In Figure 11(a) we show the revenue trajectories while in Figure 11(b), we show their profit ratios. What is remarkable is that all four firms, move into the area of losses during this period. Despite the growth of IBM, as is well known it almost bankrupted itself in the early 1990s when destructive changes in computer technology and the market for software and services drove it into loss (from which it splendidly recovered due to quite massive restructuring). General Motors too moved into loss in the early 1990s and then recovered which is indicative perhaps of what is now happening to the auto industry in general as its role in the economy changes and as its command over vehicle technologies is eroded by foreign competition, low wages offshore and automation. Lockheed Martin has much lower profits than these two forms but it too moves into losses in the early 1990s after the end of the cold war Bethlehem Steel is quite classic in its patterning in that it makes respectable profits until the 1970s when it is driven into losses as it loses market share eventually to disappear from the top 100 in 1991.



(a)



(b)

Figure 11: (a) Revenue and (b) Profit Clocks for Four Key Firms in the Fortune 100

Red – Bethlehem Steel: Green – General Motors:
Blue – IBM: Grey –Lockheed Martin

Preliminary Conclusions and Next Steps

What is quite clear from this analysis as well as from conceptual reflection on the behavior of firms during this period is that dominance measured by size and performance measured by profit ratios are only two of perhaps several indicators that need to be considered when looking at this general question of how the economy renews and adapts itself to competition and innovation marked by this coevolving nexus of creation and destruction. In terms of visualization, we now need to extend rank clocks and rank spaces to embrace the idea of more than one index being ranked, so that we might watch what happens to firms as their dominance and performance and perhaps productivity co-evolve over time.

Although the idea of rank clocks is eminently useful in visualizing the micro-dynamics of systems where it is clear that very rapid changes take place but within an envelope of apparent macro stability, there are still important difficulties in getting representations of such systems whose micro-dynamics can be tracked in a coherent and effective way. It is no accident that we have restricted our analysis to the top 100 firms for as we to move to, say, 500 firms, then the dynamics of the clock itself can be more confusing suggesting the need for a much more considered set of measures of the morphology of the clock and ways of classifying the trajectories of firms. For really large data sets, where we are talking about more than 1000 firms, things get even more difficult while for data sets with hundreds of thousands of firms, then the rank clock idea is no longer tenable although measures derived from it maybe. Moreover, as one scales the data set, then the use of the software in more routine ways to extract firm trajectories and to engender multiple comparisons from these becomes important.

In terms of the period we have examined, we have avoided the last ten years where data is available because of the very rapid changes that took place during the dot.com boom. From a preliminary examination of the more recent data over the last 10 years, it is clear that our analysis reveals much greater change for each time unit than during the previous 40 years, and this would give more power to our thesis that firm size and profits/earnings ratios provide good measures of the processes of creation and destruction. However even in this data, only now does it appear that the staple industries of the last 50 years in the US economy, particularly automobiles and similar manufactured goods, are giving way to services of many kinds as the forces of creation and destruction gather pace in the global economy and as new forms of consumer product generate new markets. We intend to extend the work reported here to capture these current events and trends, continuing to elaborate the methodologies for visualization that we have introduced here.

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