

THE EFFECT OF COMPANY SIZE ON THE PRODUCTIVITY IMPACT OF INFORMATION TECHNOLOGY INVESTMENTS

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ABSTRACT

There is much discussion in popular literature about how small to medium sized firms (SME) drive the U.S. economy. This literature points to SMEs as a primary source of innovation and job growth. It is difficult to understand the role of IT in these positive contributions because published research tends to use aggregate data. This makes it difficult to understand the underlying economic dynamics, and therefore makes it difficult to develop sophisticated IT investment policies. In this paper, 1992 and 1997 manufacturing data for the Los Angeles Metropolitan Area are stratified according to company size to allow the examination of the impact of information technology investment. This examination is carried out in the context of a statistical physics model. The analysis of the stratified data maps organizational change parameters onto layers based on company size. A proxy operating temperature (T) and its normalized inverse bureaucratic factor (β) are assigned to each company size layer. It is demonstrated that a Boltzmann distribution approximately describes the number of companies as a function of the sales per company. Comparison of the theory with the consolidated Los Angeles metropolitan statistical areas shows that the temperature T of the distribution changes between the two years, and that the magnitude of the change is correlated with company size. The change in productivity between 1992 and 1997 is correlated with company size and with IT investments. Based on the results, an information technology index is proposed to help companies assess their IT investments.

Starling Hunter acted as the senior editor for this paper.

INTRODUCTION

The need for a study of the effect of company size on the impact of information technology investments on productivity arises from a rich literature base in management information systems. The use of a statistical physics framework for this study arises from past successes in applying this framework to a variety of fields, including economics. Both of these statements are discussed further in this Section.

Management information systems literature

It is often claimed that small and medium sized businesses are responsible for most of the job and economic growth in the United States. See, for example, (Birch 1988) and (Audretsch 2004). Yet in past discussions of the impact of information technology (IT) on productivity growth, the effect of company size, per se, has not been systematically addressed. The paper that comes closest to addressing this question is (Brynjolfsson, Malone, Gurbaxani, and Kambil 1994). These authors were interested specifically in whether IT investments result in a reduction in firm size, and they concluded that this was indeed the case. They also concluded that IT investments resulted in a decline in the sales per firm and in the value added per firm. We shall see in the last two sections of this paper that our results don't necessarily support these conclusions, but that the trends themselves depend on the starting sizes of the firms.

The basic hypothesis of this paper is that the productivity impact of information technology investments depends on the size of the companies making the investment. This is because IT investment decisions are most likely based on different expectations in different size companies. We contend that this size dependence provides a straightforward means of further understanding what used to be referred to as the IT "productivity paradox".

For over a decade two schools of thought have struggled with the concept of the IT investment "productivity paradox". One school, production economics, has been driven by the hypothesis that IT investment is an input into a firm's production function. For example, the five following papers (Loveman

CONTRIBUTION

This paper demonstrates that the impact of investments in information technology on a company's output and productivity depends on the size of the company. Many government policy shifts are being driven by the belief that the small to medium size enterprise (SME) acts as an economic engine. These shifts are occurring at a time when there is little published data on the critical factors necessary to foster the creation and growth of this valuable SME economic resource. One area that is particularly not well understood is the impact of IT on the strategic issues of greater entrepreneurial focus and increased agility. It is possible that SMEs use IT and modern management theories to focus their firms on growth rather than productivity improvements of internal processes. In a time when there is attention focused on job creation, this would be a valuable insight for policy makers.

1988; Brynjolfsson 1993; Brynjolfsson and Hitt 1996; Lee and Barua 1999; Mukhopadhyay, Lerch, and Manjal 1997) provide extensive examinations of production measures in their research. The other school, which is process oriented, develops models that examine hypothetical relationships between output performance, including efficiency and quality, and IT and other input factors at various levels of aggregation in many dimensions. As examples, several papers (Kauffman and Kreibel 1991; Banker & Kauffman 1988; Barua, Kreibel, and Mukhopadhyay 1995) have focused on the impact of IT investment on intermediate variables, such as capacity utilization, inventory turnover, relative prices, and product quality.

Ultimately both camps have convinced themselves that IT investments do have a positive impact on company productivity (Brynjolfsson and Hitt 1993, 1996), (Lichtenberg 1995), (Barua and Lee 1997). However, the role of company size has not been specifically addressed.

IT has also been explored in the context of complementarity theory (Barua, Lee, and

Whinston 1996) , (Milgrom and Roberts 1990), (Hitt and Brynjolfsson 1997), and (Barua and Whinston 1998). Complementarity addresses the synergy between IT in the context of other related factors of business culture. This is the area of work that we feel has the most promise. It can overcome the problems associated with a reductionist analysis on aggregate data across diverse industries, diverse corporate cultures, and diverse firm size.

In addition, we feel that there is room for integration between these theories and the work on organizational complexity being done at MIT by (Forrester 1971) and (Sterman 1989). No firm knows the instantaneous value of costs or sales. Any numbers used will be out of date by the time they are collected, analyzed and published. Any delay in the collection of data makes the analysis of productivity nonlinear in nature and therefore any cause and effect analysis non trivial. When faced with evidence that every firm is unique and that this uniqueness is dynamic, we must fully explore the complementarity approach in a systems context. We believe that company size plays an important role in any cause and effect analysis.

Mintzberg in the early 1990's developed a framework for company forms using vectors to show the conflicting forces that an enterprise or firm must balance in order to be competitive (Mintzberg 1991). Within a given industry every company with its unique corporate culture is constantly monitoring these changing forces and trying to find the optimum combination of these forces on which to base its strategy for competitive advantage. A natural extension of company uniqueness is the premise that productivity and profitability, while present in most business forms, are not uniformly emphasized throughout an industry. This brings us to the fundamental question as to how to develop a context for this problem that is of a form that is simple enough to understand and at the same time robust enough to be useful in guiding strategic decisions. Again, we believe that company size is important in determining the optimum combination of external forces that a company uses to determine its competitive strategy.

Statistical Physics

Statistical physics was developed during the nineteenth century to describe systems containing a large number of entities. In such systems, the large number of entities present makes it virtually impossible to obtain an exact description of how each is behaving. Statistical physics solves this dilemma by looking only at the most probable behavior instead of the exact actual behavior of the system.

For example, suppose that a system consists of a large number of particles with a total energy of some specified value. Statistical physics employs a straightforward technique for determining the most probable way that the energy is distributed among the particles. The essence of this technique is to identify the most probable distribution as that corresponding to the largest possible number of arrangements of the particles. (For instance, if one distribution can be realized by a million different possible arrangements of the particles, and another distribution can only be realized by a thousand different arrangements, the first would be expected to be much more probable.) This leads to the famous Maxwell-Boltzmann distribution in which the probability that a particle has any specified energy is inversely proportional to the exponential of that energy.

The technique for obtaining the most probable distribution is known as "constrained maximization". It is "constrained" by the requirement that the total energy and number of entities is that which was specified originally, and it employs "maximization" to obtain the distribution that corresponds to the maximum possible number of arrangements of the entities. In statistical physics, it can be demonstrated that the resulting most probable distribution is a very good description of the real situation when the number of entities in the system is very large.

We shall apply the constrained maximization technique of statistical physics to the economic realm, with the understanding that we are looking at only the most probable behavior of an economics system rather than its exact actual behavior.

This application of statistical physics to economics follows in the tradition of a long-term association between economics and physics. This association can be found in both neoclassical economics and modern new growth economics. According to Smith and Foley both neoclassical economics and classical thermodynamics seek to describe natural systems in terms of solutions to constrained optimization problems (Smith and Foley 2002). The interdisciplinary new growth (ecological) economic theories provide IT with a promising set of frameworks. Costanza, Perrings and Cleveland argue that two very different fields of science initially drove the development of new growth economic models: thermodynamics and biology (Costanza, Cleveland and Perrings 1997). Thome and London use Open System Thermodynamics to study large displacements of economic disequilibrium (Thome and London 2000).

The remainder of this paper is organized as follows: The next section provides the statistical physics approach. Following that section, the U.S. Economic Census LACMSA is summarized. In the final section of the paper, the size-dependent results are discussed.

STATISTICAL PHYSICS APPROACH

As described in the previous section, in the statistical physics formalism, the most likely distribution of a large number of entities consistent with a few specified total values is obtained by maximizing the number of ways in which the entities can be arranged to give the specified total values.

For example, in a physical system consisting of a specified number of particles with a total specified energy, this procedure gives the exponential Boltzmann distribution with only one undetermined parameter, the temperature. This distribution is obtained by maximizing the number of ways the particles can be arranged among energy states subject to the constraints that the total number of particles is fixed and the total energy is known. These constraints are usually taken into account by the mathematical technique of Lagrange multipliers.

It is useful to point out a salient feature of the foregoing approach that gives rise to a Boltzmann distribution. Specifically, only one quantity was maximized: the number of ways the particles could be arranged subject to the constraints.

In previous papers, we have illustrated the application of the statistical physics formalism to economics by considering (1) the distribution of output vs. employee productivity (Dozier and Chang 2004a). and (2) the distribution of output vs unit cost of production (Dozier and Chang 2004b).

The distribution of output vs unit cost was shown to satisfy a Boltzmann distribution, with the number of units produced being exponentially dependent on the unit cost of production. The Boltzmann distribution is appealing because of its simple exponential dependence. However, it appears to be difficult to compare the predictions of the theory with actual data, because unit cost of production data is not readily available..

By contrast, the distribution of output vs employee productivity was found to satisfy a nonexponential distribution that exhibited a maximum in output at some preferred value of productivity. It also displayed a maximum in employee number at a preferred value of productivity. Data on productivity is readily available, so it is easier to test the theoretical predictions. Indeed, a preliminary comparison with 1992 and 1997 U.S. economic census productivity data for the consolidated metropolitan statistical areas of the Los Angeles area gave encouraging results. On the other hand, there are two undesirable features of the derived productivity distribution: (1) First, it was derived following an unconventional variation of the statistical physics formalism, and (2) the independent variable (productivity) does not display the invariant quality that the usual independent variables of statistical physics that give Boltzmann distributions do. The unconventional variation consisted of maximizing the product of two quantities: the number of ways the output could be distributed among the different sites, times the number of ways the employees could be distributed among the sites.

In the following, we shall instead derive an economics Boltzmann distribution by maximizing only one quantity. The independent variable will be the sales (shipments) per company, and the quantity that will be maximized is the number of ways companies can be distributed over different values of sales per company. This is of particular interest in connection with the oft-cited statistic that most of the companies in California are small businesses.

Table 1 summarizes the basic equivalences that exist between the economics quantities of this paper and the conventional quantities in the physical realm, as a result of applying the constrained maximization technique of statistical physics to both fields.

In the economics realm, the role of energy per entity in the physics realm is replaced by sales per company. The Boltzmann distribution in physics that gives the most probable number of entities with a specified energy will be replaced by a Boltzmann distribution giving the most probable number of companies with some specified sales.

In the following, it will be shown that just as there is a temperature that describes how broadly energy is distributed in physical systems, there is a “temperature” that describes how broadly sales is distributed over companies. It is also possible to introduce other “thermodynamic” analogues, such as entropy, free energy, etc., but since they are not central to the conclusions of this paper, we shall not do so here.

Suppose, then, that there are a large number of companies N .

Denote by $n(S)$ the number of companies that each have a sales output S . In that case,

$$N = \sum n(S) \tag{1}$$

Then the total sales of the N companies is

$$S(\text{total}) = \sum S n(S) \tag{2}$$

where in both eqs. (1) and (2) the summation is from $i = 1$ to $i = N$.

With the foregoing assumptions, we now ask what the most likely distribution of companies $n(S)$ is over the sales per company S .

The number of ways that N can be arranged is $N!$. However, not all of these ways are consistent with the assumed distribution $n(S)$. The number of ways $n(S)$ can be arranged is itself $n(S)!$ and each of these is equivalent as far as counting the number of ways that N can be arranged. Thus, the total number of allowable ways that N can be arranged subject to an assumed distribution $n(S)$ is:

$$P(N, n(S)) = N! / (n(S_1)!n(S_2)! \dots) \\ = N! / \prod n(S)! \tag{3}$$

where the \prod in the denominator denotes the product of all the $n(S)!$'s. To deal with a sum rather than the product, we employ the conventional statistical physics technique of forming

$$\ln \{P[N, n(S)]\} = \ln\{N!\} - \sum \ln\{n(S)!\} \tag{4}$$

Assuming that $n(S)$ is large, Stirling's approximation can be used for the logarithm of a factorial:

$$\ln \{n!\} \Rightarrow n \ln \{n\} - n \Rightarrow n \ln \{n\} \tag{5}$$

Thus,

$$\ln \{P(N, n(S))\} \Rightarrow N \ln \{N\} - \sum n(S) \ln \{n(S)\} \tag{6}$$

where the summation is over all possible S .

Table 1. Equivalent basic statistical variables in economics and physics

Physics	Economics
Energy	Sales
Number of entities with given energy	Number of companies with given sales

The most probable distribution of $n(S)$ will be that for which $\ln\{P(N, n(S))\}$ has a maximum, i.e. for which the derivatives $d \ln\{P(N, n(S))\}/dn(S) = 0$. However, we must also take into account the constraints of eqs.(1) and (2). This can be done by introducing Lagrange multipliers α and β to form

$$F(n(S)) = \ln\{([N, n(S)])\} - \alpha(\sum n(S) - N) - \beta(\sum S n(S) - S(\text{total})) \quad (7)$$

When the constraints of eqs. (1) and (2) are satisfied, the multipliers of α and β in this equation are both zero, so that eqs. (6) and (7) are equivalent. The quantities α and β can be adjusted to assure that their multipliers are in fact zero.

Then, on setting

$$dF(n(S)) /dn(S) = 0 \quad (8)$$

to determine the distribution that maximizes the number of possible arrangements, we find as the condition for a maximum of $\ln \{P(N, n(S))\}$ subject to the constraints of eqs. (1) and (2):

$$- \ln\{n(S)\} - 1 - \alpha - \beta S = 0 \quad (9)$$

Solving eq. [9] for $n(S)$, we find

$$n(S) = A \exp(-\beta S) \quad (10)$$

where

$$A = \exp(- (1+\alpha)) \quad (11)$$

is an undetermined constant that can be expressed in terms of N and β . Thus, if the sum is replaced by an integral over S from 0 to ∞ , then

$$A = \beta N \quad (12)$$

i.e. the number of companies with company sales in the interval $(S, S+dS)$ is

$$n(S)dS = \beta N \exp(-\beta S)dS \quad (13)$$

and the total number of sales $S(S)dS$ in the interval $(S, S+dS)$ is

$$S(S)dS = \beta N S \exp(-\beta S)dS \quad (14)$$

Figures 1 and 2 depict $n(S)/\beta N$ and $S(S)/\beta N$ for $\beta = 0.5, 1, \text{ and } 5$.

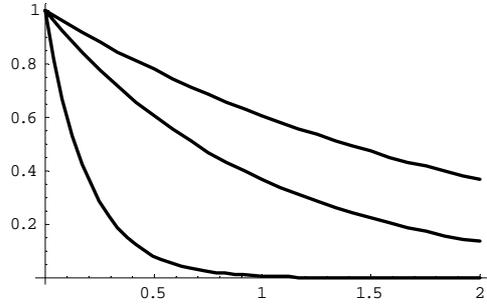


Figure 1. The (normalized) distribution of companies $n(S) / \beta N$ vs shipments per company S for $\beta = 0.5$ (top curve), 1 (middle curve), and 5 (lowest curve)

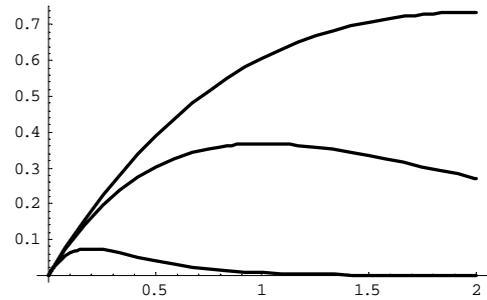


Figure 2. The (normalized) distribution of shipments $S(S)/\beta N$ vs shipments per company S for $\beta = 0.5$ (top curve), 1 (middle curve), and 5 (lowest curve)

As in the examples for the two previous applications, the parameter β indicates the degree of randomness in the collection of companies.

Thus, the procedure leads to a simple exponential dependence of the number of companies $n(S)$ on the shipments per company S , and a distribution with a maximum for the shipments as a function of the shipments per company S .

A quantity that is less sensitive to the idiosyncrasies of specific companies is the cumulative number of companies that have shipments/company less than or equal to a given value of shipments/company:

$$N(S) = \int n(s)ds = \int \beta N \exp(-\beta s)ds = N(1-\exp(-\beta S)) \quad (15)$$

where the integration is from $s=0$ to $s=S$. The integration over $n(s)$ averages over variations due to company-specific idiosyncrasies.

The figure below displays $N(S)$ vs shipments per company S for three different values of β .

Plots of the cumulative distributions of companies vs shipments per company might be expected to depend on the IT investments of the companies included in the plots. The IT investments would be expected to impact both the overall magnitudes of the shipments as well as how the “temperature” of the distributions. In the next section, this impact will be illustrated with actual data.

COMPARISON WITH US ECONOMIC CENSUS DATA

The U.S. economic census data base for 1992 and 1997 provides a good source for determining the three basic statistical physics parameters described in the previous Section (number of companies, temperature, and shipments) for different collections of companies (U.S. Census Bureau 1992 and U.S. Census Bureau 1997). Our focus in the following will be on the sectors comprising the manufacturing activity in the Los Angeles consolidated metropolitan statistical area (LACMSA). The three parameters, and their change in values between 1992 and 1997, will be seen to be different for collections of companies with different sizes. The tie-in with information technology investments is provided by economic census data on these manufacturing sectors at the national level: in the following, it will be seen that these data show a correlation between the percentage of expenses expended by companies on information technology and the size of the companies.

There are 134 major manufacturing sectors represented in LACMSA.

Figure 4 displays the relation between IT rank (which designates how likely a company in a particular sector is to invest in information technology) and the percentage of expenses dedicated to data processing and software. It is interesting that for IT expense percentages less than about 20%, the relation

between the rankings and the percentages is practically linear.

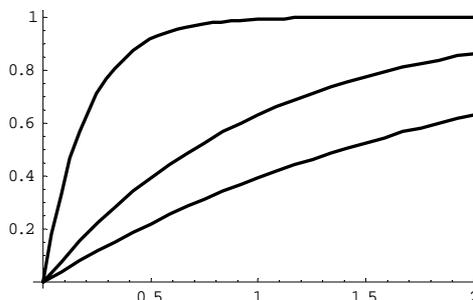


Figure 3. The (normalized) cumulative distribution of companies $N(S)/N$ vs shipments per company S for $\beta = 0.5$ (bottom curve), 1 (middle curve), and 5 (top curve). Here the normalization factor N denotes the total number of companies.

Our interest is in both the values of the three statistical physics parameters and their change between 1992 and 1997, and any correlation between these quantities, IT ranking, and company size. For LACMSA, the data is not available for both 1992 and 1997 for all of the 134 manufacturing sectors in the area. Of the 134 sectors, complete data is contained in the U.S. economic census for both 1992 and 1997 for only 76 sectors. Accordingly, we have focused our attention on these 76 sectors.

The reason for the lack of complete data for both 1992 and 1997 for all 134 manufacturing sectors is not apparent to us. It may be due in part to overlap problems created by the change between the manufacturing categories that the U.S. Department of Commerce used in 1992 and 1997. In 1992, the classification was according to the old Standard Industrial Classification system, whereas in 1997, the classification was according to the North American Industry Classification System (NAICS).

Although the statistics is not as good as would have been the case if it would have been possible to include all 134 sectors, the 76 sectors included in the analysis provide a good cross section of the manufacturing activity in the Los Angeles basin. Future studies will not be hampered by the change in the

classification system that occurred between 1992 and 1997 and should have even better statistics.

It is of interest at this point to compare the cumulative distribution of companies in these 76 sectors with that predicted in Figure 3 by the statistical physics model of the previous Section. The differential distribution of the data corresponding to Figure 1 shows much more scatter due to the idiosyncrasies of the individual sector. The scatter is diminished in the cumulative distribution, since the integration involved in forming the cumulative distribution averages out the idiosyncrasies of the individual sectors.

Figures 5 and 6 show the cumulative number of companies vs shipments/company in \$million (diamond points) as well as the cumulative distribution curve (square points) of eq. (15) for 1992 and 1997, respectively. To obtain a good fit with the data, we have chosen the statistical physics β to be 0.167 per 10^6 for 1992 and 0.125 per 10^6 for 1997.

Two things are noteworthy about these two Figures.

1. The fit of the statistical physics curve of eq. (15) to the observed U.S. economic census data is fairly good. The 76 points provided by the data and the integration involved in the formation of the cumulative distribution are sufficient to provide a reasonable statistical fit, averaging out the idiosyncrasies of specific sectors.
2. Apparently, β for the 76 Los Angeles manufacturing sectors decreased in the five years between 1992 and 1997. This corresponds to an increase in the statistical physics temperature of the manufacturing activity in Los Angeles – i.e. there was more variability in the company behavior in 1997 than in 1992.

To study the impact of company size on the effects of IT expenditures, we divide the 76 sectors into three categories:

- L: the 26 sectors containing the largest companies
- I: the 26 sectors containing the intermediate size companies
- S: the 24 sectors containing the smallest companies.

and examine the data for each of the three groups separately.

For these three size groups, the average IT rankings are L: 59; I: 70; and S: 81. Sectors with the largest companies have dedicated a larger percentage of their business expenses to information technology that the smallest companies – although the difference is not very dramatic.

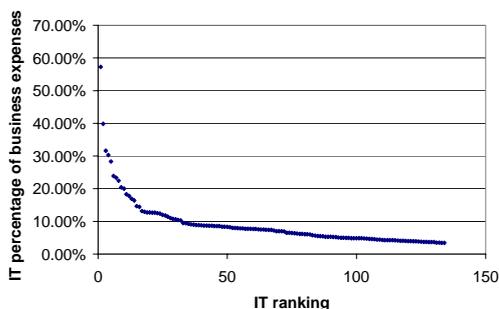


Figure 4. Relation between IT rank and the percentage of business expenses devoted to data processing and software for the 134 major manufacturing sectors in LACMSA

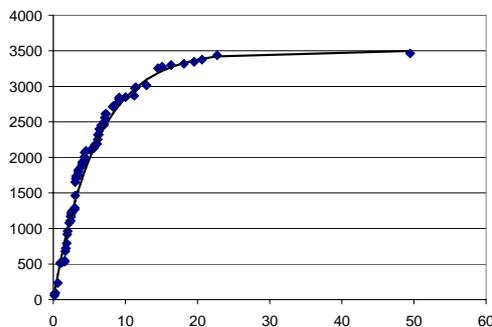


Figure 5. Comparison of U.S. economic census cumulative number of companies vs shipments/company in \$M (diamond points) in LACMSA in 1992 and the statistical physics cumulative distribution curve (solid line) of eq. (15) with $\beta = 0.167$ per 10^6

Curves similar to the ones in Figures 5 and 6 can be plotted for each of these three size groups.

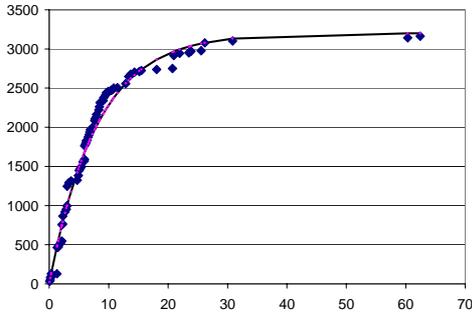


Figure 6. Comparison of U.S. economic census cumulative number of companies vs shipments/company in \$M (diamond points) in LACMSA in 1997 and the statistical physics cumulative distribution curve (solid line) of eq. (15) with $\beta = 0.125$ per $\$10^6$

Figure 7 shows the corresponding curves for the 26 largest company sectors for 1992 and 1997. Figure 8 shows the plots for the 26 intermediate company sectors. Figure 9 shows the curves for the 24 smallest company sectors.

The fits for the individual size sectors are not as good as those for the larger sample of 76, but are adequate to allow a best-fit determination of the three statistical parameters of the previous Section.

At the same time, we note that the curves for the intermediate size companies tend to be more S-shaped than predicted by the statistical physics formalism. This may be associated with the fact that the collection of intermediate size companies really cannot be treated as a closed system: rather, it gains as small companies grow and also as large companies diminish in size, and it loses as intermediate size companies fail. (S-shaped curves in the time domain also occur in the dynamic realm – not treated here – when positive and negative feedback loops compete and when start-up, shakeout, and saturation phenomena are important.)

The salient results are summarized in Table 2.

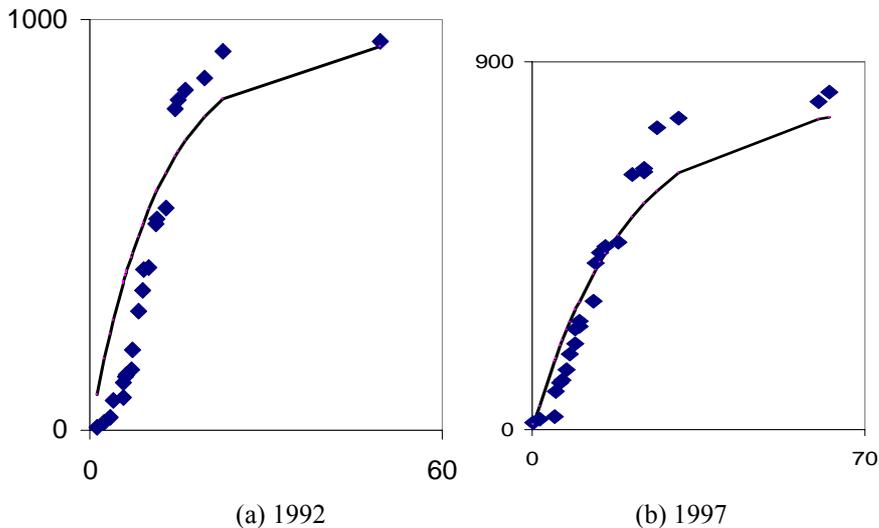


Figure 7. Comparison of U.S. economic census cumulative number of companies vs shipments/company in \$M (diamond points) in LACMSA in 1992 and 1997 for the 26 largest company size sectors, and the statistical physics cumulative distribution curves (solid line) of eq. (15). For 1992 the comparison curve has $\beta = 0.083$ per $\$10^6$, while for 1997 the comparison curve has $\beta = 0.06$ per $\$10^6$.

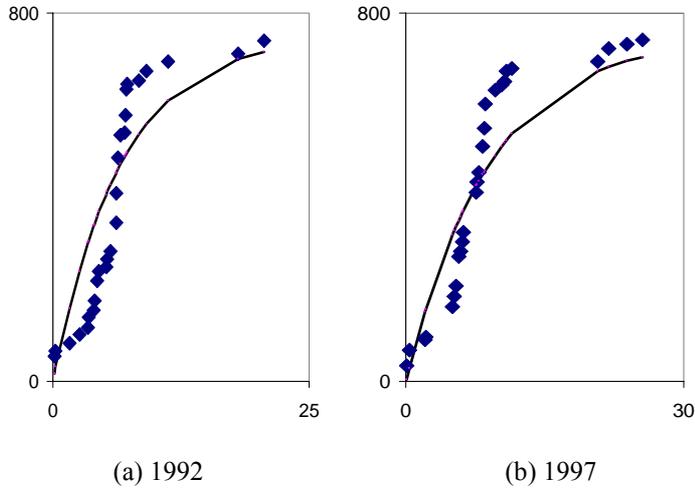


Figure 8. Comparison of U.S. economic census cumulative number of companies vs shipments/company in \$M (diamond points) in LACMSA in 1992 and 1997 for the 26 intermediate company size sectors, and the statistical physics cumulative distribution curves (solid line) of eq. (15). For 1992 the comparison curve has $\beta = 0.15$ per 10^6 , while for 1997 the comparison curve has $\beta = 0.11$ per 10^6 .

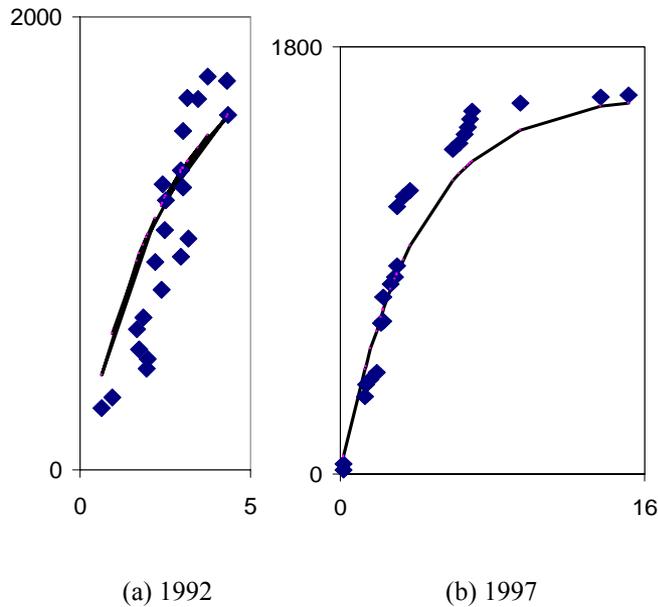


Figure 9. Comparison of U.S. economic census cumulative number of companies vs shipments/company in \$M (diamond points) in LACMSA in 1992 and 1997 for the 24 smallest company size sectors, and the statistical physics cumulative distribution curves (solid line) of eq. (15). For 1992 the comparison curve has $\beta = 0.4$ per 10^6 , while for 1997 the comparison curve has $\beta = 0.25$ per 10^6 .

Table 2. Summary parameters for the 76 manufacturing sectors in LACMSA, divided according to the three sector segments: (Large) segment with 26 largest average company sizes; (Intermediate) segment with 26 intermediate average company sizes; and (Small) segment with smallest average company sizes. The parameters are given for both 1992 and 1997

Company size	Large		Intermediate		Small	
	1992	1997	1992	1997	1992	1997
Census year	1992	1997	1992	1997	1992	1997
IT rank	59		70		81	
Number of companies	968	834	739	741	1778	1598
Sector employees (1000s)	154	120	40	40	43	46
Employees/company	159	144	54	54	24	29
Sector sales (\$million)	23,240	35,589	4625	5751	3868	5507
Sales/employee (\$1000)	106	176	114	153	90	121
Inverse temperature β (1/\$million)	0.08	0.05	0.15	0.11	0.4	0.25
Bureaucratic factor $\underline{\beta} = \beta \times \text{sales/employee}$	1.92	2.13	0.94	0.85	0.87	0.86

Note that the bureaucratic factor $\underline{\beta}$ measures the variance of the sales per company normalized to the average sales per company for the company size group.

Table 3 gives the ratios of the various parameters (1997 parameter/1992 parameter).

In the Tables, the number of companies, the total shipments, and β are the statistical physics parameters of Section 3, whereas the number of employees and the productivity (sales per employee) are the statistical physics parameters in our earlier treatment (Dozier and Chang 2004b)

The Figures show that considerable dispersion exists in the behavior of the different manufacturing sectors. Nevertheless, the definite averages of the foregoing Tables can be defined for different groups. For example, the difference in the averages of the sectors with different size companies is significant even though the dispersion within each sector is large. This is so since the groups are separated from each other by a well-determined parameter (size, in this case), and a particular datum point is not being used to determine in which group a particular sector belongs. In other words, the averages stated

Table 3. Ratio ('97/'92) of the segment characterization parameters

Company size	Large	Intermediate	Small
Sector companies ratio	0.86	1.0	0.90
Sector employees ratio	0.78	0.98	1.08
Employees/company ratio	0.91	1.0	1.21
Sector sales ratio	1.53	1.24	1.42
Sales per employee ratio	1.66	1.34	1.35
Inverse temperature (β) ratio	0.6	0.73	0.62
Bureaucratic factor $\underline{\beta}$ ratio	1.11	0.90	0.99

are for well-defined groups. At the same time, however, it should be kept in mind that considerable dispersion does occur within each group.

CONCLUSIONS

The statistical physics formalism provides a useful framework for discussing the behavior of collections of companies. It focuses attention on a few salient parameters while at the same time showing how the parameters enter into measurable distributions. As applied in this paper, the formalism combined with LACMSA data describe some interesting phenomena:

IT expenditures and company size

On average, sectors with the larger companies dedicate a larger percentage of their business expenses to information technology than smaller companies (an average of 8% compared to 6%).

Decrease in number of companies

Except for the sectors with intermediate company size, the number of companies decreased on the order of 10% between 1992 and 1997.

Decrease in number of employees

The sectors with the large companies decreased close to 20% in total number of employees, while the sectors with intermediate size companies remained almost level in employment, and the sectors with the small company sizes increased total employee count by about 8%. Overall, however, the number of employees in the 76 manufacturing sectors studied decreased between 1992 and 1997.

Company size increase

The small company size group showed an increase in average company size between 1992 and 1997 (about a 20% increase). The average company size in the intermediate size group remained constant. The large company size group showed about a 10% decrease in average company size.

Shipment increase All three company size segments showed an increase in shipments in 1997, with the large company sectors showing the largest percentage increase (although the increase in the small company group was not far behind).

Productivity increase All three size segments showed an increase in productivity (shipments/employee) between 1992 and 1997. The largest percentage increase occurred for the segment with the largest companies (a 66% increase), while the segments with small and intermediate size companies both showed about a 35% increase.

It is interesting that the sector segment that showed the largest productivity increase and the largest percentage increase in shipments is the segment that had the largest percentage investment in information technology. This could be due to the direct effects of information technology. At the same time, it could also be due to a difference in objectives between large and small companies: larger companies may invest in IT primarily to increase productivity, whereas smaller companies may have other objectives in mind, e.g. to increase market breadth.

Temperature

The variability of manufacturing company behavior in the Los Angeles area appears to have increased between 1992 and 1997, corresponding to an increase in temperature ($1/\beta$) of 67% for the collection of sectors with the largest and the smallest companies, and an increase in temperature of 37% for sectors with the intermediate size companies. The temperature of the collection of sectors with the largest companies is over four times that of the collection of sectors with the smallest companies, since the shipments per company is so much larger for the collection of sectors with the largest companies.

Bureaucratic factor β

If the distribution functions of Section 2 were used instead with a normalized shipments/company (in which shipments/company was replaced by shipments per company divided by the average shipments per company for the group), then the group with the largest companies has the lowest effective temperature. This is probably of more interest than β itself since it is a direct measure of the ratio of the variance of the distribution to the mean, i.e. it is a better indicator of the shape of the distribution curve.

We believe the variance of the normalized shipments per company designated by β is related to the degree of bureaucracy in the group: the higher the bureaucracy, the less

variance there is in the behavior. Thus, Table 1 shows that the largest companies have the largest bureaucratic factor β , as might be expected. Indeed, the β for the large company group is approximately twice as large as those for the intermediate and small company size groups. The magnitudes of the β 's also indicate that the variances are of the same order of magnitude as the associated means.

Table 2 shows that between 1992 and 1997, the bureaucratic factor increased by 10% in the large company size group, while decreasing by 10% in the intermediate size company group, and remaining practically the same in the small company size group.

IT index It is apparent from the economic census data that different manufacturing sectors spend different percentages of their budgets on information technology. These percentages range from a little over 3% to almost 60%. For the management of a particular company, these percentages – which may be regarded as an “IT index” - may provide a useful guide for determining how the company's IT expenditures compare with those of the competition.

Overall, we believe these results provide some support for our hypothesis that company size is an important parameter in understanding how IT investments impact a company's performance. At the same time, we would recommend further studies with a broader data base in order to obtain better statistics: Application of the statistical physics framework to the complete U.S. economic census for 1997 and 2002 would be a good candidate for a future study. The improved

statistics from the larger data base can also provide opportunities for further data stratification, e.g., by subgroups of NAICS categories.

Besides the impact on productivity, this brief study has also suggested that IT investments should be analyzed in terms of their impact on total sales and on total employment. Again, for these parameters, it appears important to stratify the data according to company size.

Although not specifically addressed in this paper, we believe that the quasi-static statistical physics approach of this paper can be extended to provide a good framework for understanding dynamic phenomena in company behavior. It should provide a starting point for virtual model simulations that help understand the complicated feedback loops and nonlinear effects that are present in unstable oscillations in inventories of interdependent companies.

Finally, we believe that the “IT index” suggested by the study may prove to be a useful strategic guide to an individual company as a measure of how the IT investment of the company compares with others in its size group.

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REFERENCES

- Applegate, L. M., F.W. McFarlan, and J.L. McKenney, *Corporate Information Systems Management: Text and Cases*, Irwin, Burr Ridge, IL., 2002.
- Audretsch, David B., "Sustaining Innovation and Growth: Public Policy Support for Entrepreneurship," *Industry and Innovation*, 2004, 11, pp. 167-191
- Banker, R. D., and R.J. Kauffman, "Strategic contributions of information technology: an empirical study of ATM machines," *Proc. 9th International Conference on Information Systems*, 1988, pp.141-150
- Barua, A., C. H. Kreibel, and T. Mukhopadhyay, "Information technologies and business value: An analytical and empirical investigation," *Information Systems Research*, 1995, 6(1): pp. 3-23.
- Barua, A., S. Lee, and A. B. Whinston. "The calculus of reengineering," *Information Systems Research*, 1996, Vol. 7(No. 4), pp. 409-728

- Barua, A. and B. Lee, "The IT productivity paradox revisited: A theoretical and empirical investigation of the manufacturing sector." *The International Journal of Flexible Manufacturing Systems*, 1997, Vol. 9, pp. 145-166.
- Barua, A. and A. B. Whinston, "Complementarity based decision support for managing organizational design dynamics." *Decision Support Systems*, 1998, 22, pp. 45-58.
- Barua, A. and T. Mukhopadhyay, "Information Technology and Business Performance: Past, Present, and Future," Zmud (ed.), *Framing the Domains of IT Management Projecting the Future. Through the Past. B*, Pinnaflex Education Resources, Inc, Norman Oklahoma, 2000, pp 65-84
- Birch, David L., "The Hidden Economy," *Chief Executive*, 1988, 45, pp. 30-35
- Brynjolfsson, E., "The Productivity Paradox of Information Technology: Review and Assessment." *Communications of the ACM*, December 1993, 35(12), pp. 66-77
- Brynjolfsson, E. and L. M. Hitt, "Is information systems spending productive? New evidence and new results," *Fourteenth International Conference on Information Systems*, Orlando, FL., 1993
- Brynjolfsson, E., T.W. Malone, V. Gurbaxani, and A. Kambil, "Does information technology lead to smaller firm size?" *Management Science*, 1994, 40(12), pp.1628-1644
- Brynjolfsson, E. and L. Hitt, "Paradox Lost? Firm-level evidence of the returns to information systems spending." *Management Science*. 1996, 42, pp. 541-558.
- Brynjolfsson, E., A. Renshaw, M. Van Alstyne., "The Matrix of Change." *Sloan Management Review* (Winter 1997), 38:2, MIT Press, Cambridge, Mass
- Costanza, R., C. Cleveland, and C. Perrings, *The Development of Ecological Economics*, Edward Elgar Publishing, Cheltenham, UK, 1997
- Dozier, K., and D. Chang, "A statistical physics model of technology transfer." *Technology Transfer Conference*, 2004a, Albany, New York
- Dozier, K., and D. Chang , "Thermodynamics of productivity framework for impacts of information/communication investments," *CITSA 04-ISAS 04, Orlando Conference*, 2004b.
- Forrester, J. W., "Counterintuitive behavior of social systems," *Technology Review*, 1971, 73(3): 52-68.
- Hitt, L. M. and E. Brynjolfsson, "Information technology and internal firm organization: An exploratory analysis." *Journal of Management Information Systems*, (Fall 1997). Vol. 14, No. 2, pp. 81-101
- Kauffman, R. J. and C. H. Kreibel, "Identifying business value linkages for production processes involving information technology," in Y. Kin and V. Srinivasan.(eds.), *Advances in Working Capital Management, Vol. 2, A Research Annual*, JAI Press Inc., Greenwich, CT, 1991, pp. 67-93
- Lee, B. and A. Barua, "Assessing productivity and efficiency impacts of information technologies: Old data, new analysis and evidence," *Journal of Productivity Analysis*, 1999, 12(1) pp. 21-43.
- Lichtenberg, F. R., "The output contributions of computer equipment and personnel: firm level analysis," *Economics of Innovation and New Technology*, 1995, 3, pp. 207-217.
- Loveman, G. W., "An assessment of the productivity impact of information technologies," in T. J. Allen and M. S. Scott-Morton (eds.), *Information Technology and the Corporation of the 1990's: Research Studies*, MIT Press, Cambridge, MA, 1988, pp. 84-110
- Milgrom, P. and J. Roberts, "The economics of modern manufacturing: Technology, strategy and organization," *American Economic Review*, 1980, 80 pp. 511-528.
- Mintzberg, H., "The Effective Organization: Forces and Forms," *Sloan Management Review* (Winter 1991), pp. 54-67
- Mukhopadhyay, T., F. J. Lerch, and B. Manjal, "Assessing the impact of information technology on labor productivity- a field study." *Decision Support Systems*, 1997, 19(2), pp. 109-122.
- Smith, E. and D. Foley, *Classical thermodynamics and economic general equilibrium theory*, New School for Social Research White Paper, November 19, 2002, New School University, 65th Ave., New York, NY, pp. 1-28
- Sterman, J., "Misperceptions of feedback in dynamic decision making." *Organizational Behavior and Human Decision Processes*, 1989, 43(3), pp. 301-335
- Thome, F.A., and Silvia London, "Disequilibrium economics and development," *Computing in Economics and Finance*, 2000, paper number 377

U.S. Economic Census Results 1992, <http://www.census.gov/epcd/www/92result.html> , last accessed January 15, 2006

U.S. Economic Census Results 1997, http://www.census.gov/epcd/ec97/us/US000_31.HTML, last accessed January 15, 2006

Zmud, R. W., *Framing the Domains of IT Management: Projecting the Future. Through the Past*, Pinnaflex, Cincinnati, OH, 2000

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