ROI Projection Results for E-Portfolios

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Abstract

Many communities have taken interest in developing technology companies in their region. Technology companies are known to bring higher average salaries, skilled workers, and increases in tax base. In this paper, we develop and use an analytical method to predict how companies grow and what specific affects this may have on a local region. The method begins by identifying the types of companies likely to succeed in the region. Then, it allows for the prediction of growth variables including job creation, ROI for investors, and ROI for the community. As an illustration, the paper compares the long-term effects of launching 1, 5, 10, 15, and 20 companies per year for 15 years sequentially. The results are provided in terms of job creation and ROI for a wide range of confidence intervals.

1. Introduction

Many communities and regions have taken interest in developing technology companies for the purpose of economic development. Technology companies are known to bring higher average salaries, skilled workers, and increases in tax base. Further, many of these communities have invested on the growth of start-ups with the hope of larger paybacks to the community and the investors. To ascertain the returns from these investments, we first need to know the answers to two fundamental questions: First, which types of companies are most likely to succeed within that geographic region? Second, how will a region grow based on specific investments in new technology companies?

In this paper we provide answers for both these questions. This paper combines prior work of the authors to develop analytical models to address these two questions (Sidhu et al., 2003; Shariff et al., 2003). This paper leverages both of these earlier models to present a methodology to estimate the expected ROI from E-portfolio's of technology companies. The analytical models are illustrated using a case study. The theoretical frameworks of both models are briefly described in this paper, with greater emphasis given to the combination of the results from the two models to interpret the potential for growth in the region and hence the return from investments made on the E-portfolios in the region.

An E-*Portfolio* is defined as a collection of companies started in a region. To gain a high return on investments on an E-portfolio, it is necessary to find out which types of companies are most likely to succeed within the geographic region and the growth pattern of the regional economy. The first analysis technique shown in this paper is used precisely for this purpose (Shariff et al., 2003). The Capability Market (C-M) matrix model is a simple tool for analyzing the strengths of a community to assess which types of companies are most likely to succeed within that region and to distinguish the relative strengths of a region based on the available talent pool in that region. The model is illustrated using the Champaign-Urbana case. The results from the CM Matrix model help policy makers to decide on which companies to invest and incubate in the local region. Once this decision is made, the following model can be used to answer the second question.

The second model is the predictive growth model (Sidhu, et al., 2003). This analytical model explains how companies grow and quantifies the returns obtained on the E-portfolio to the investors as well as the community. In this paper the predictive model is illustrated with an example and the results obtained by using the models are presented. In the following section we begin by reviewing the theoretical foundations of the CM Matrix model first and then the predictive model. Although the illustrations used in both these models are not from the same case study, but if it is to be applied to a local region or community, the analysis could follow the same sequence as explained in this paper.

2. Evaluating Strengths of a community- C-M Matrix Model

Policy makers have taken interest in developing technology companies in their region. The key question before investing is: which types of companies are most suitable for growth in their community. This question is answered by using the Capability-Market matrix model. The Capability-Market matrix is a unique way of representing the economic clustering in a region, by grouping the professionals in the region based on their capabilities as well as the markets they serve. This section of the paper will illustrate the C-M Matrix model using the Champaign-Urbana case.

This section, briefly describes the theoretical framework of the CM matrix method for analyzing which types of companies are most likely to succeed within a geographic region. An illustration of a CM matrix is shown in Figure 1. The columns represent the different markets segments serving the employee pool of a region for example retail, transportation, healthcare etc. The rows represent categories of the capabilities such as software development, consulting and system integration, civil and construction etc. In the illustration the value in cell (2,2) represents the strength of the cluster of people with similar capability (i.e., capability 2) in a particular market type (i.e. market 2).

2.1 Theoretical Framework

To formulate a CM matrix, assume a set of n companies in the target area where economic development is desired. There are n companies (i.e., *company 1*, *company 2,…*, *company n*) each of size x_i employees, where $1 \leq i \leq n$. The vector c_{ij} represents the n_c potential capabilities of company i, where $1 \leq j \leq n_c$. The vector m_{ij} represents the n_m potential markets which they may serve, where $1 \leq k \leq n_m$.

The capability vector c_{ij} for company i has elements representing the fraction of the company's capability across the set of technology capabilities, where j is an index for capability. Similarly, for company $i,$ a market vector indexed by k, partitions the space of market relationship types ($1 \leq i \leq n_c$; $1 \leq j \leq n_m$). Completely partitioned sets of capabilities and markets must satisfy Equations (1) and (2), respectively.

$$\sum_{j=1}^{n_c} c_{ij} = 1; \forall i \text{ --(Eqn. 1)}$$

$$\sum_{k=1}^{n_m} c_{ik} = 1; \forall i \text{ --(Eqn. 2)}$$

Let the total population of workers in the area be x, which is the sum of x_i over all companies.

$$x = \sum_{i=1}^{n} x_i \text{ --- (Eqn. 3)}$$

The capability vector for the entire target area is $C=(C_1, C_2 ... C_{n_c})$ indexed by j within the range $1 \leq j \leq n_c$ of which the elements are:

$$C_j = \frac{\sum_{i=1}^{n} x_i c_{ij}}{x} \text{ ---------------------------------------(Eqn. 4)}$$

Consequently the market vector for the entire target area is M = $(M_1, M_2 ... M_{n_m})$ indexed by k within the range $1 \leq k \leq n_m$ of which the elements are:

$$M_k = \frac{\sum_{i=1}^{n} x_i m_{ik}}{x} \text{ -------------------------------------(Eqn. 5)}$$

Using the capability vector C and the market vector M the Capability-Market matrix for the target area considered can be derived as shown in Equation (6), below. In the following section, we will discuss the results of applying this framework to the Champaign- Urbana, Illinois region.

$$CM = \begin{bmatrix} C_1 M_1 & C_1 M_2 & \ldots & C_1 M_{n_m} \\ C_2 M_1 & C_2 M_2 & \ldots & C_2 M_{n_m} \\ \ldots & \ldots & C_j M_k & \ldots \\ C_{n_c} M_1 & C_{n_c} M_2 & \ldots & C_{n_c} M_{n_m} \end{bmatrix} \text{-----(Eqn. 6)}$$

2.2 Capability-Market (CM) Matrix Case Study

The CM matrix is a highly effective tool to analyze the strengths of a region based on the regions capabilities in terms of professional talent available and the markets they currently serve. The CM matrix is demonstrated in this section by considering 75 technology companies that either originated or are headquartered in the Champaign-Urbana, Illinois region. The original list of companies was taken from year 2001-2002 Advanced Technology Directory of Champaign County Economic Development Corporation (www.cupartnership.org) and then supplemented with phone interviews and web based research.

The sample being studied comprises of 2595 people working in the technology sector comprised of a list of 75 technology companies in Champaign-Urbana. In Table 1, we show the Capability-Market matrix for the Champaign Urbana region. From the CM formulation, we can estimate, for example, that there are approximately 334 people in the regional economy, who work in businesses that develop software for government markets.

This sample set of capabilities (Software, Hardware…) and markets/industries (consumer, transportations, healthcare…) represent only one possible set of partitions.[1] Our choice of market segmentation was chosen to closely correspond with that of Gross National Product (GNP) classification from the U.S. census bureau.[2]

The Capability Market matrix is also a unique way of representing the economic clustering in a region. Because worker salaries are generally the larger portions of operating budgets for technology companies, these elements represent relative magnitudes of the regional economy by business capability and market. The sums of the rows represent skill resources, which exist in the regional area. Any row with a large sum represents a relative strength in capability. Weaker columns in any such row represent an area, which is conducive for growth. The sums of the columns represent strength of distribution channels and relationships with certain customer categories. A column with large sum indicates that many people with different specializations are serving that market. The larger numbers in the matrix represent hot spots for the regional economy.

From the CM matrix we may infer, on a relative basis, that Software is the largest capability strength. Hardware, civil/construction, and system integration are running a distant but relatively equal second place in magnitude. We may also infer that the government and educational markets represent the largest category of customers for the products of the local economy. We suggest that this matrix is more suitable intermediate tool for estimating the capabilities and potential growth patterns of a regional economy than portfolio management tools.

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[1] In future study, we intend to investigate other alternative capability and market sets.
[2] This classification is commonly referred to as NAIC.

In examining the CM matrix in this case study; we can make the following recommendations. First, in terms of critical mass of regional capabilities, we note software and system integration makes up 57.2% of the high tech community's capability. Civil/construction, hardware, and industrial manufacturing make up 15.4%, 12.9%, and 7% percent respectively. Companies with these skills make up over 96% of the high tech workforce. Conversely, chemical, biomedical, agricultural, materials, and food science are not significant in the current job marketplace. Second, from a market point of view 55.5% of the technology economy sells to government and educational markets. An additional 11.8%, 10.9%, and 7% are attributed to retail, transportation, and healthcare respectively for technology companies. Again less than 4% of the technology company economy sells to healthcare, finance, and agriculture combined. Third, there is a difference between industry leadership and academic leadership. In university settings for example, these distinctions are not always clear. Suggestions of leadership in areas like biosciences or nanotechnology can be tested against actual economic metrics to understand how much economic activity already exists in areas known for thought leadership.

For policy makers trying to grow an E-portfolio in the Champaign-Urbana region, the CM Matrix model outlines the relative strengths of the region based on the capabilities of the region and the markets currently being served. Based on the results of the CM Matrix Model the growth pattern of the regional economy can be inferred. In the next section of the paper we describe the predictive growth model to predict how companies grow and what specific effects this may have on a local region. The analysis uses two inter-related models. The first is a general model for characterizing company growth and the second characterizes the resources invested over time for creating new businesses.

3. The Predictive Growth Model

In this section, we briefly describe the theoretical framework used for studying growth of a region based on specific investments in new technology companies within that region and the ROI obtained by the investors and the community. We begin by studying the growth characteristics of a portfolio of companies and what specific affect this may have on the local region.

3.1 Theoretical Framework

To define the *Portfolio* concept, let $X_i(t)$ be a random process specifying the number of employees for company i in year t after its inception. $X_{Portfolio}(t)$ is a random process, it characterizes the total number of employees within the *Portfolio* as a function of time. $\mu(t)$ is the mean and $\sigma(t)$ is the standard deviation, response functions of the random process $X_i(t)$.

Another important model in this framework is the investment profile, which describes how many companies can be started over the course of future years based on limitations, including investments. We define an investment profile as a function $g(t)$, which is the number of companies enabled by investment in year t. For example $g(t)$= [1,1,1,1] means that one company will be started each year for the next 4 years. In general, if θ companies can be launched every year, the policy can then be expressed as:

$$g(t) = \theta \sum_{a=0}^{\infty} \delta(t-a) \text{ -------------------------------------- (Eqn. 7)}$$

Next, we predict the growth pattern of the *Portfolio* based on any given mean response function, deviation response function, and investment profile. Let $g(t)$ be a particular investment profile. Figure 2 shows a forecasting table for the number of employees in the *Portfolio*. In the example, g(t) = [1, 2, 1…] Also, as implied by g(0) = 1, there is one company launched at time zero and it will have $X_1(1)$, $X_1(2)$, $X_1(3)$ … employees at the end of the company's first, second, thirds, etc year of operation respectively.

We can calculate the total number of employees in each year for the *Portfolio* by taking the sum down any given column of the table - as in the equation below. Note that the variable a is used to index the investment profile $g(t)$.

$$X_{Portfolio}(t) = \sum_{a=0}^{\infty} \sum_{b=1}^{g(a)} X_i(t-a) \text{ --------------------- (Eqn. 8)}$$

From this relation it can be shown that the expected value and variance of the number of employees in the *Portfolio* is the convolution of the mean and variance response functions with the investment profile, we may use the standard notation for convolution (Sidhu et al, 2003). The distribution of $X_{Portfolio}$ approaches the Normal distribution as the number of companies in the *Portfolio* grows larger, by the Central Limit Theorem. Remember, $X_{Portfolio}(t)$ is the weighted sum of independent random variables for any given value of t. Specifically, we may approximate the distribution as follows: $X_{portfolio}(t) \sim N[\mu_{portfolio}(t), \sigma_{portfolio}(t)]$.

3.2 Predictive Growth Model Case Study

3.2.1 Data Collection and Interpretation

Based on the above theoretical framework and earlier data collected by the authors (Sidhu et al., 2003), the Mean Response functions for High Growth and Marginal Start-Ups are compared in Figure 3. As we would expect, high growth companies have higher expected numbers of employees and growth rates. For high growth companies, most of the growth is in the first 5 years, after which growth is relatively flat. For marginal companies, our simulation indicates a relatively flat growth in the first 5-10 years and the possibility of larger company sizes as the company matures. Similarly the Deviation Response functions are compared in Figure 4. As expected, with age, companies disperse in size and their deviations become greater. High growth companies tend to have greater variances than marginal growth companies.

Based on collected data and analysis techniques outlined here and discussed in more detail in (Sidhu et al., 2003), we plot the growth projections for the region in the portfolio analysis form by deriving the mean and standard deviation of the number of employees in the entire *Portfolio* given various investment profiles. The case study tests 5 different investment profiles for launching high growth companies and compares the results using standard financial portfolio theory:

1) One company launched every year for 15 years and then no more investments
2) Five companies launched every year for 15 years and then no more investments
3) Ten companies launched every year for 15 years and then no more investments
4) Fifteen companies launched every year for 15 years and then no more investments
5) Twenty companies launched every year for 15 years and then no more investments

The graphs in Figures 5 and 6 are obtained by convolving the mean and variance response functions (from Section 3.1) with each of the five above specified investment profiles. Our intention in this example is to predict the size and variability of the *Portfolio* during and after the end of 15 years of consistent investment in growth oriented companies. Each curve represents a different number of years into the investment process. For example, the "two year" curve has 5 points. The five points on this curve (and all other curves) give the statistics for the number of employees in the *Portfolio*. The point on each curve specifies statistics depending on whether 1, 5, 10, 15 or 20 companies were launched each year. Statistics for 1 company per year is the point being closest to the origin and 20 companies per year point being farthest away – on each line. Even though investments were made for 15 years in a row, we evaluated the *Portfolio* across a 25-year window, because we wanted to see the effects of the investments in years following the investment itself. The graphs are separated into two so that detail can be observed in early years.

From the graphs we deduce the mean number of employees as the Return for the *Portfolio* and the standard deviation as a measure of risk. Any point with a higher mean for the same deviation is a better choice. Similarly, any point with a lower deviation given the same mean is a better investment alternative. Any line in the first quadrant through the origin represents constant return to risk ratio. Points higher or to the left would be better investments. From the graphs, we can see that greater numbers of companies per year reduce risk for a given return in a marginally decreasing manner – as we would expect. A final illustration provided in this section is that of the actual growth pattern of the *Portfolio* over time. In Figure 7, we examine the increasing numbers of mean employees in the *Portfolio* given that 15 new companies are launched per year for 10 years. We note that after the 15th year, which is 5 years after the last investment, the growth has reached a plateau. In particular, we note that the function, might be grossly approximated by a growth line from years 1 though 15 and a flat line from year 15 to the end of the simulation window. The authors have noted similar gross characteristics with the other investment profiles as well.

3.2.2 Analysis of Growth Prediction Model Case Study

The growth projections from the growth performance curves for the region are then tested within certain confidence intervals as shown in Table 2. In order to provide a simple mapping between the growth of the *Portfolio* and the returns to the investors as well as the community we suggest the following method based on our choice of employee count as the driving intermediate variable:

1. Construct table estimating *Portfolio* size based potential investment profiles as shown in Table 2.
2. Normalize table by number of investments made within the Champaign-Urbana region.
3. Develop multipliers to determine ROI for investors and the Champaign-Urbana community

The first sub-table in Table 2 (third and fourth columns) shows values for a 50% confidence interval - this means that with a probability of ½, there will be at least this many employees in the *Portfolio*. The next sub-table (fifth and sixth columns) provides the same statistical information, but with an 84% confidence interval. Finally, the last sub-table provides the most stringent confidence interval of 97%.[3]

Our final step is to develop multipliers for the Champaign-Urbana case study, which relates company size per investment to ROI for the investor, and ROI for the community. For the community, we will consider the primary increase of long-term jobs and money, which circulates within the regional economy based on the new job creation. We will also consider the money circulation caused by the investments in the community and also consider the secondary effect of increased demand for marginal businesses due to the primary increase in money circulation. Similar multipliers are also used while calculating the ROI for investors. For investors and the companies they invest in, the sensitivity of the multipliers would depend on factors such as technology and industry type. It will also depend on the average salaries of the region because regions with higher costs of living will need to spend proportionately greater amounts in their budgets for human capital. This is described in our earlier work (Sidhu et al., 2003). Our interest here is in the application of those results in the theoretical models and will discuss more about

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[3] Note that these confidence intervals (50%, 84% and 97%) represent the tail probabilities of an event that the number of employees is less than 0,1, and 2 standard deviation below the mean for the random process, $X_{Portfolio}(t)$, when t is large enough where a steady state number of employees has been reached.

the results obtained as a result of the analysis. The results of our analysis in calculating the multipliers for the Champaign-Urbana region are shown in Table 3. The multipliers are used to evaluate the ROI, which is interpreted by the relation: Jobs per investment * multiplier = ROI. Applying these multipliers we can calculate the ROI as shown in Table 4. For example an investment profile, where you start one company per year, the return to the community will be 981% at 50% confidence interval, which is larger than the return/investment figure due to the long-term effects of the money circulating in the economy as discussed above. At 84.1% confidence interval the ROI to the community is 277%.

In order to analyze sensitivities to other variables (e.g. annual salary, dollars invested per company, and company valuation per employee), different multipliers may be chosen using the analysis shown in our previous work (Sidhu et al., 2003). This section demonstrates that the growth of the region can be analyzed with a single concise economic model using characteristic functions of mean and deviation response to predict sample statistical properties of a regions growth.

4. Summary

In this paper we have shown the use of two analytical models to create a growth model for a region or community. Both the questions of: which companies are most likely to grow and what are the effects of this on the growth patterns of the region, have been addressed using the C-M Matrix model and the Predictive growth model respectively. We've illustrated both the models using the Champaign-Urbana case example.

The two case illustrations described in this paper show how growth characteristics and ROI can be quantitatively predicted for the Champaign-Urbana region. Furthermore, we showed which industries in particular are more receptive to growth than others. From the CM matrix we may infer, on a relative basis, that software is the largest capability strength. Hardware, civil/construction, and system integration are equal second place in magnitude. Companies with these skills make up close to 90% of the high tech workforce in the Champaign-Urbana region. In terms of markets it serves, government and educational markets is the biggest customer for companies in the region. In the case study for growth prediction we see direct results for five possible investment profiles covering a period of 15 years of investment. We observed reductions in risk from diversification across greater numbers of investments. We also observed large returns on behalf of the Champaign-Urbana community as opposed to only the investors.

We also acknowledge the scope for improving the models, for example for the C-M matrix model the sample set of capabilities and markets chosen in the Champaign-Urbana case study represent only one possible set of partitions. And in the predictive growth model we've not considered the influence of external factors while creating a growth model for the region. These could be areas of extension for this research.

5. REFERNCES:

1. Shariff, S., Diaz, F., Yassine, A., Sidhu I., "*Capability-Market Matrix Analysis for Economic Development Policy*", IEEE Engineering Management Conference Proceedings, Albany, NY, 2003.
2. Sidhu, I., Yassine, A., Shariff, S., "*Predictive model for New Venture-Based Region Growth*", Working paper, Technology Entrepreneur Center, University of Illinois at Urbana-Champaign, 2003.

6. ILLUSTRATIONS

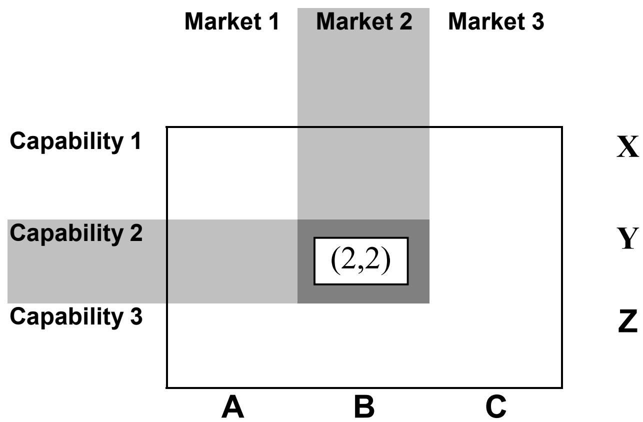

Figure 1: Capability-Market Matrix Illustration

Years	1	2	3	4	5	6	7	8	……
$g(0)=1$	$X_1(1)$	$X_1(2)$	$X_1(3)$	$X_1(4)$	$X_1(5)$	$X_1(6)$	$X_1(7)$	$X_1(8)$	
$g(1)=2$		$X_2(1)$ $X_3(1)$	$X_2(2)$ $X_3(2)$	$X_2(3)$ $X_3(3)$	$X_2(4)$ $X_3(4)$	$X_2(5)$ $X_3(5)$	$X_2(6)$ $X_3(6)$	$X_2(7)$ $X_3(7)$	
$g(2)=1$			$X_4(1)$	$X_4(2)$	$X_4(3)$	$X_4(4)$	$X_4(5)$	$X_4(6)$	
… …									

Figure 2: Forecasting Table

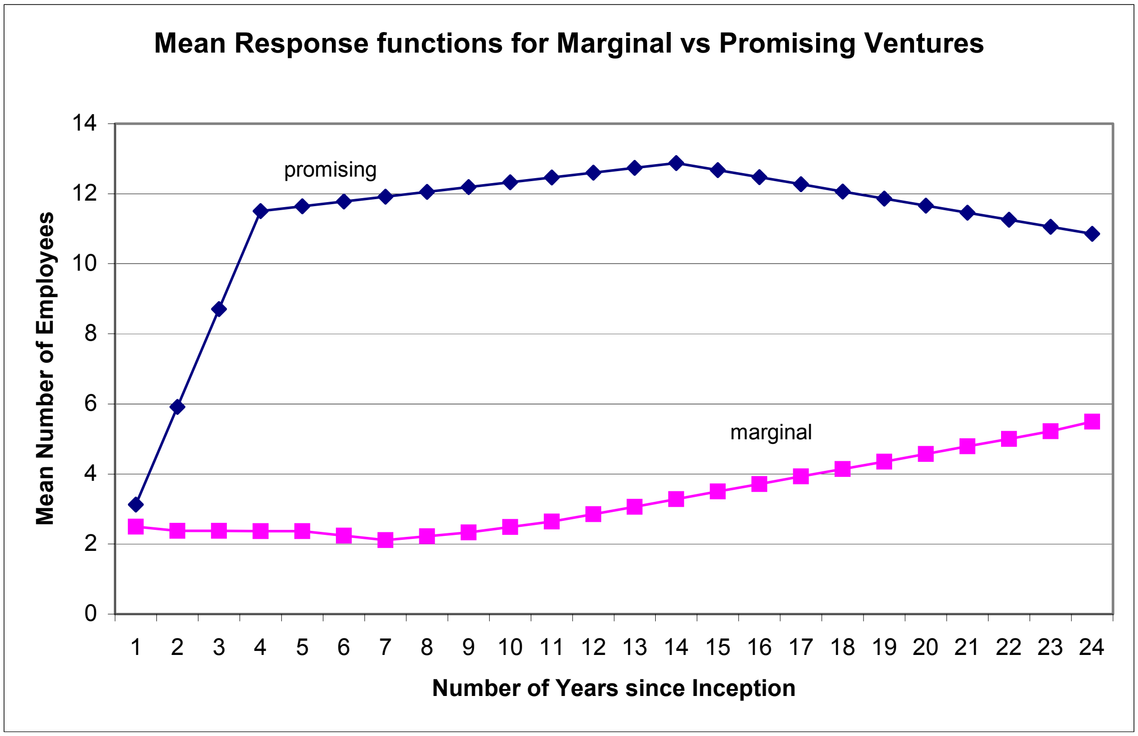

Figure 3: Mean response functions for marginal Vs promising ventures

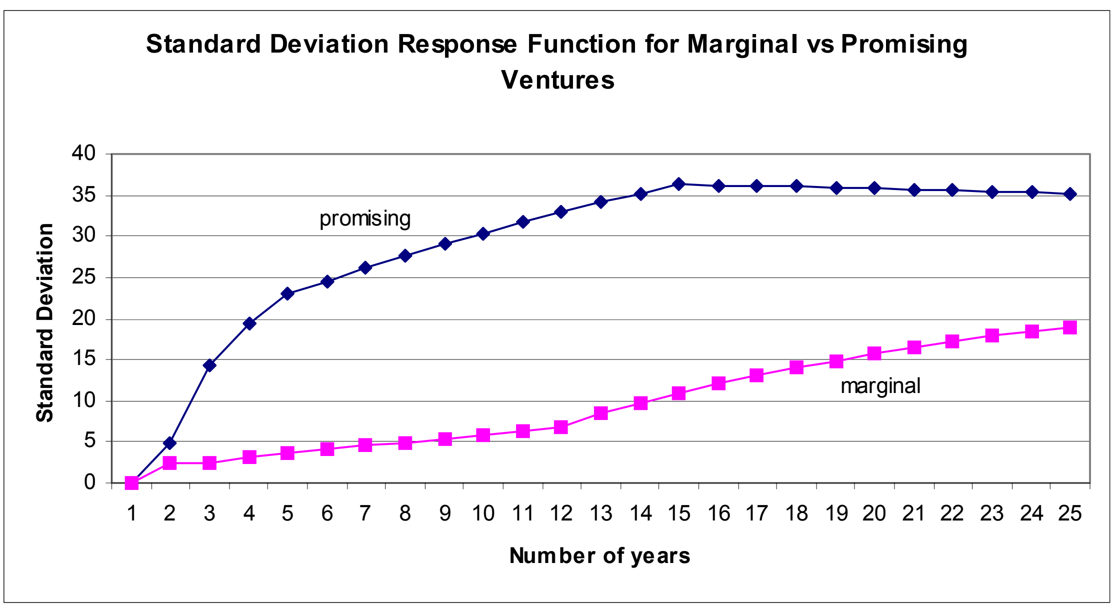

Figure 4: Deviation response functions for marginal Vs promising ventures

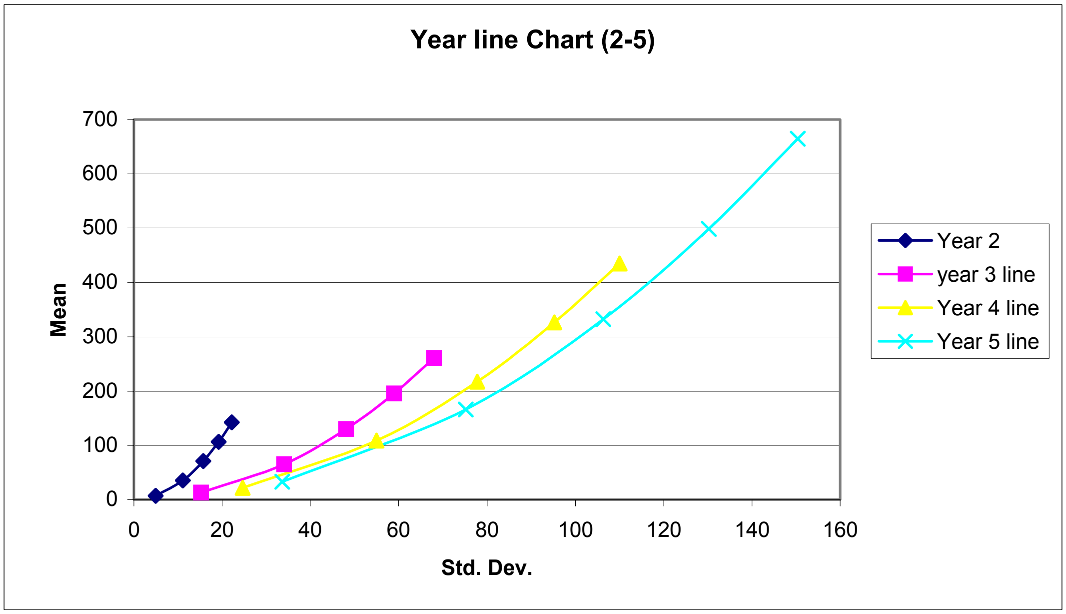

Figure 5: Growth Curves for Different Investment Profiles

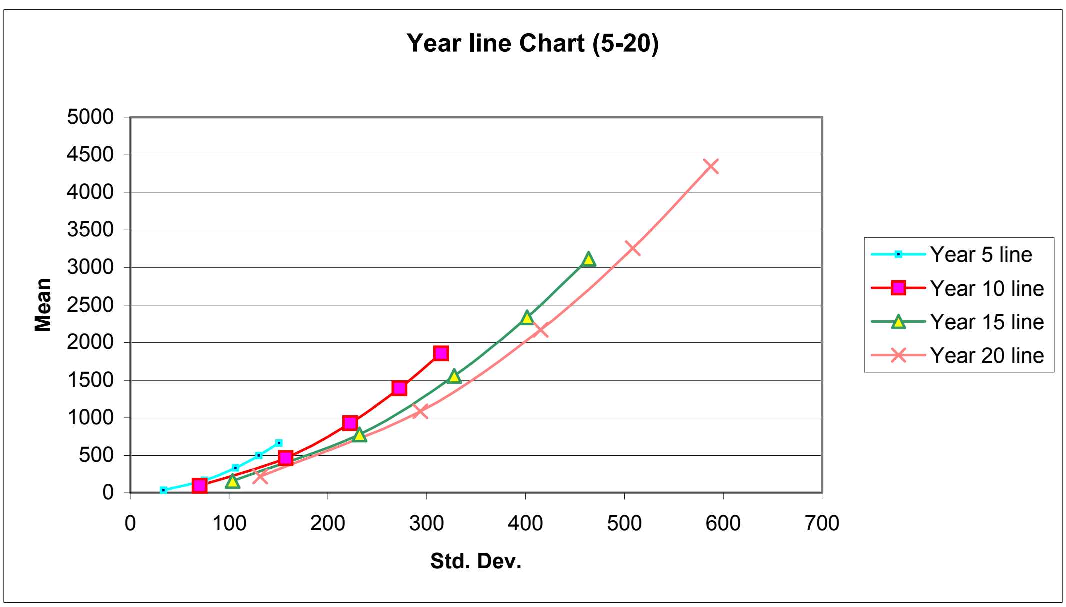

Figure 6: Growth Curves for different Investment Profiles between Year 5 and 20

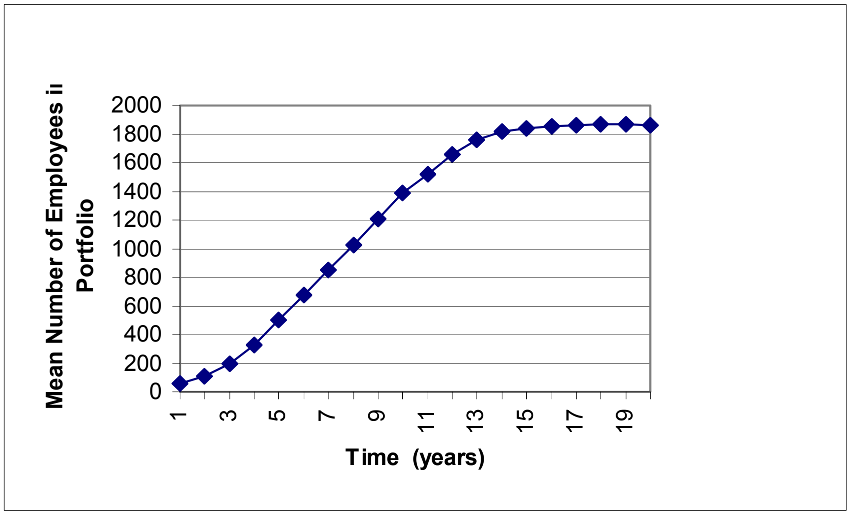

Figure 7: Fifteen Companies Launched per Year for 10 Sequential Years

	Retail Trade	Transportation	Health Care	IT & Telecom	Gov/Milt	Educational Services	Agricultural Group	Finance & Insurance	Sum
Software	123.42	94.42	83.30	111.69	333.66	245.27	14.50	35.94	1042.2
Hardware/Device	39.66	30.34	26.77	35.89	107.22	78.81	4.66	11.55	334.9
Chemical/Biomedical	6.21	4.75	4.19	5.62	16.78	12.33	0.73	1.81	52.4
Civil/Construction	47.37	36.24	31.97	42.87	128.06	94.13	5.56	13.80	400
Industrial/Systems	21.66	16.57	14.62	19.60	58.56	43.04	2.54	6.31	182.9
Consulting/System Inte	52.34	40.04	35.33	47.37	141.51	104.02	6.15	15.24	442
Data & Technical Serv. (	12.85	9.83	8.67	11.63	34.74	25.53	1.51	3.74	108.5
Agricultural/Food Sci.	1.01	0.77	0.68	0.91	2.72	2.00	0.12	0.29	8.5
Materials & Other	2.79	2.14	1.89	2.53	7.56	5.55	0.33	0.81	23.6
Number of Employees	307.3	235.1	207.4	278.1	830.8	610.7	36.1	89.5	2595

Table 1: CM Matrix for the Champaign-Urbana Case

Investment Profile	Companies Launched	Confidence Interval: 50% (Jobs | Jobs/Invest)		Confidence Interval: 84% (Jobs | Jobs/Invest)		Confidence Interval: 97% (Jobs | Jobs/Invest)	
1	15	184	12.27	52	3.47	0	0.00
5	75	920	12.27	547	7.29	315	4.20
10	150	1839	12.26	1230	8.20	902	6.01
15	225	2759	12.26	1935	8.60	1534	6.82
20	300	3678	12.26	2652	8.84	2188	7.29

Table 2: Simulation Data Table

ROI Category	Multiplier
Investors	1.57
Community	1.8
Investors and community	1.25

Table 3: Multipliers used for the Champaign-Urbana Case Study

Confidence Interval: 50%				F = .3	F=.57	F=.8	F=1.25	F=1.5
Investment Profile (IP)	Companies Launched	LT Jobs	Jobs per Investment		(Investor)	(Comm.)	(Comm + Multiplier)	
1	15	184	12.27	368%	699%	981%	1533%	3067%
5	75	920	12.27	368%	699%	981%	1533%	3067%
10	150	1839	12.26	368%	699%	981%	1533%	3065%
15	225	2759	12.26	368%	699%	981%	1533%	3066%
20	300	3678	12.26	368%	699%	981%	1533%	3065%
Confidence Interval: 84.1%								
IP	Companies Launched	LT Jobs	Jobs per Investment					
1	15	52	3.47	104%	198%	277%	433%	867%
5	75	547	7.29	219%	416%	583%	912%	1823%
10	150	1230	8.20	246%	467%	656%	1025%	2050%
15	225	1935	8.60	258%	490%	688%	1075%	2150%
20	300	2652	8.84	265%	504%	707%	1105%	2210%
Confidence Interval: 97.7%								
IP	Companies Launched	LT Jobs	Jobs per Investment					
1	15	0	0.00	0%	0%	0%	0%	0%
5	75	315	4.20	126%	239%	336%	525%	1050%
10	150	902	6.01	180%	343%	481%	752%	1503%
15	225	1534	6.82	205%	389%	545%	852%	1704%
20	300	2188	7.29	219%	416%	583%	912%	1823%

Table 4: Return on Investment for Various Multipliers and Confidence Interval Ranges