The Relationship Between R&D and Patents: An Econometric and Event-Time Analysis

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ABSTRACT

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This research paper will attempt to describe and explain the relationship between corporate R&D investments and the output of this investment i.e. patents. The first section of the thesis describes the empirical relationship between R&D and patents using standard econometric techniques, and then compares these results with results from a nonparametric technique called locally weighted regression that makes only general assumptions regarding the shape of the regression function. Throughout the analysis, careful attention is payed to the specification of lag structure. In terms of in-sample goodnesss-of-fit and out-of-sample forecasting performance, several parametric models perform well and all models are dominated by the nonparametric procedure with suitably chosen smoothing parameters.

The second section of the thesis employs standard event study techniques to investigate whether capital markets favourably perceive these innovative activities. Using a wide variety of R&D and new product announcements from the 1980's, it is found that markets do not respond to announcements of R&D investment changes, although they do reward announcements of new products, which can be viewed as the output of successful R&D.

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INTRODUCTION

Many researchers have investigated the recent apparent decline of U.S. economic performance, relative to other industrialized countries. One factor that has been suggested as a primary cause of this economic decline is the lack of spending on research and development by U.S. firms. While the U.S. spends more on research and development in total than the Japanese, Germans, French and the United Kingdom put together, the problem has been that 80% of this outlay is devoted to military programs which also engage a large portion of the nation's engineers. As a result, the U.S. currently trails Japan and the Germans in non-defense R&D as a percent of GDP.

This thesis attempts to shed some light on the relationship between research and development, the patent counts of the firm, and firm value. Theoretically, the annual research and development expenditures of firms are considered to be investments in the firm's stock of knowledge, a stock that depreciates over time as older R&D investment becomes less valuable. Patent counts are employed as indicators of the value of the additions to the stock of knowledge; as a result, patent represents the "success" or output of R&D.

The empirical analysis of the relationship between R&D and patents is challenging for several reasons. First, patents are not the only output of research and development, and industry and firm- specific differences in the method in which R&D investment affects patent output are probably substantial.

As a result, the aggregate relationship between R&D and total patents may obscure important firm and industry-specific differences. This study employs firm- specific data on patent counts and R&D expenditures (in Chapters 2-4) and in equity returns around R&D announcement dates (in Chapters 5-7) in order to provide some summary evidence on the relationship between R&D and patents while controlling for industry-specific effects.

Second, it is not clear that the relationship between R&D and patents should necessarily be contemporaneous. Patents may be the result of I.&D in stment from previous years, or may alternatively be the result of an application made in the early stages of a research project. From the perspective of economic policy, knowledge of the lag structure is important in that effectiveness of government efforts to stimulate research and development must be evaluated over the appropriate time horizon. This thesis presents a comprehensive econometric analysis of this lag structure using a variety of different techniques.

Third, theory provides very little guidance as to the appropriate functional form (irrespective of lag structure) for the relationship between patents and R&D. This thesis estimates a variety of parametric econometric models for the relationship, and then compares the results with a nonparametric procedure called locally weighted regression that makes very general assumptions about the relationship.

The parametric models considered here are standard (see Griliches, Hall, and Hausman (1986), for example); if it is the case that the nonparametric procedures dominate parametric structural models (in terms of out-of-sample forecasting performance), this would cast considerable doubt on the conclusions from previous studies employing these techniques.

In addition to a direct examination of the relationship between patents and R&D, it is possible to obtain information regarding the market's perception of the effects of R&D on firm value using standard event study techniques. Chapters 5-6 employ CRSP return data and a cross-section of R&D and new product announcements to examine this relationsnip. These techniques are advantageous in that they do not require the specification of a precise theoretical model governing the relationships between R&D and patents. Analysis of both R&D and new product announcements allows for an investigation of financial market's perceptions of the dynamics of innovative activity as well.

This thesis is organized as follows: Chapter 1 provides a brief summary of the relevant theoretical and empirical literature; Chapter 2 describes the empirical methodology underlying the direct study of patents and R&D and also presents a preliminary data analysis. Chapter 3 presents the empirical results for the first section of the thesis. Chapter 4 briefly introduces the event study methodology and describes the data used in the second section of the thesis.

Chapter 5 applies the methodology to R&D announcements, and Chapter 6 considers new product announcements. Chapter 7 concludes and suggests avenues for future research.

CHAPTER 1: RESEARCH HYPOTHESES AND THEORETICAL ANALYSIS

The first section of this thesis will attempt to analyze the relationship between R&D and patent counts. Existing theory usually employs R&D values to represent the stock of knowledge to the firm, and employs the number of patents awarded to the firm as an indicator of the output of this investment.

In order to empirically evaluate the relationship between these two variables, two factors must be considered. The first issue relates to the lag structure of the patent production function. For example, using current research and development figures to evaluate the firm's intangible 'stock of knowledge' explains only the contemporaneous relationship between the two variables. There are effects on the stock of knowledge that are the result of previous investments in research and development. Careful analysis of lag structure is important for developing a good understanding of the relationship between patents and R&D.

A second issue is that theory does not provide much guidance as to the precise functional form for the relationship. As a result, it is important to employ econometric techniques that are robust to possible mispecification along these lines. This thesis employs nonparametric techniques to investigate the relationship between patents and R&D, and also uses capital market information from R&D and new product announcements to assess the market's perception of innovative activity. In both cases, a precise parametric model for the relationship between patents, R&D, and firm value is not required.

The Research Hypotheses:

H1: Increases in innovative and/or risky R&D results in increases in the number of patents awarded to a company.

H2: Positive R&D announcements will be viewed positively by capital markets generating significant positive abnormal returns.

H3: New product announcements will be positively perceived by capital markets generating positive abnormal returns.

The first hypothesis will respond to the two issues stated previously. The econometric analysis will be discussed in chapters 2-4. The next two utilize stock price returns to gauge the market's perception of innovative activity brings a new dimension to the analysis. The discussion related to the second and third hypotheses can be found in the event-study section of this thesis in chapters 5-6.

By bringing both an internal as well as external market perception-based analysis, it is the aim of this study to develop a better understanding of the reasons behind the innovative activities of firms.

Each approach will be discussed from a theoretical framework, with the initial analysis related to the R&D-patent link. This will begin with a review of the existing literature related to hypothesis 1. These are discussed in the next section.

__The R&D-Patent Link:__

Mansfield described the first major component of R&D expenditures as basic research. This is related to long-term R&D projects[Mansfield 1984]. In essence, basic research is considered to be geared towards developing new products and processes. Depending on the area of this research, ie. its 'depth'(amount of pre-existing and related research in a particular area already in progress) and its 'breadth'(spread of R&D over different areas and/or new areas) of research, the firm's basic research may or may not be a risky component of a firm's R&D portfolio.

The majority of basic research is performed by "large firms" [Mansfield 1984]]. These companies have a substantial resource base to invest in longer-term payback timetables. In addition, for these larger firms, their size provides an insulation against their competition. This is due to the fact that they are more able to diversify their R&D programs. Thus basic research has been strongly linked to inventive output which in turn is highly correlated with patent output[Scherer 1981]. Since patents are not the only output of R&D expenditures, testing this noisy relationship is difficult.

Mansfield[1984] hypothesized that smaller firms carry out the disproportionate share of R&D. Indeed, as the R&D/asset(Rdwei) vs. assets graph(Figure 1) shows, low-asset firms perform more than their share of R&D. The inverse relationship between firm size and R&D expenditures suggests that larger firms do less proportionate research. Mansfield suggests that small firms also carry out a disproportionate share of the risky R&D aimed at new products and processes. His findings also remark that these firms place themselves at far greater risk than large corporations. Their R&D focus is narrower and absorbs a greater proportion of their cash flows. Since our sample is more homogeneously weighted towards larger firms, we did not account for potential variation across firm size.

The initial link we are making exists between the input variable R&D and the patent counts as output. Thus the following preliminary relationship is developed:

R&D -----> additions to economy ---->patents as indicator of valuable knowledge and benefits of innovation.

In this study I will examine the functional form and lag structure of the relationship between R&D and patent data. These two constructs are central components on the pathway of corporate technological innovation. The patent counts will effectively be considered the successful output of innovative R&D programs.

The difficulties of this study stem from the fact that patent counts are noisy indicators of a company's R&D [Griliches 1990]. Therefore, the R&D is only able to account for a small portion of the variance in the patent count. Thus even good models are weak predictors of the relationship.

The initial work in estimating the patent production function was done by Pakes and Griliches[1984]. Their main finding was that a significant relationship exists between contemporaneous R&D expenditures and patent counts. Subsequent studies examining patent counts have generated similar findings,(see Griliches[1990] and Hausman et. al. [1988], for example). However, the influence of lagged R&D values on patent counts was ignored in these studies. Thus the precise shape of the distributed lag remains in doubt. Using parametric and nonparametric techniques, the lag relationship will be examined in this thesis. Controls will be used to account for cross-industry differences in propensities to patent. Findings that result in the dominance of the nonparametric model over the existing parametric forms will cast doubt over the parametric results.

The existing literature suggests that in the cross-sectional tests of patenting activity R&D is 0.9 correlated to patent counts using an R^2 measure[Griliches, Hall and Pakes 1990]. The relationship was also found to be significant. The strength of this relationship suggests that patents are a strong indicator of innovative R&D programs. The Griliches study was across firms in general and not industry-specific. This also suggests that the patent output is a good indicator of R&D expenditures when a contemporaneous sample is used.

The patenting process is generally initiated during the early stages of the research project. This suggests that there are substantial R&D investments in the same area made ex poste(after) the application period. This creates additional scenarios to examine regarding the precise timing of the contribution of the stock of knowledge to the patent counts. Thus, Uri Ben-Zion makes the following statement, "there is a great deal of randomness in the timing of the successful output of the R&D process and the decision as to when and where to patent it." [Uri Ben-Zion 1984]. This contributes to the difficulties in modelling the lag structure as described by Griliches, Hausman and Hall.

This timing relationship was expanded in two studies; one by Hausman et. al.[1984] in which a significant lag effect was found in the distributed lag of R&D on patents. The study found a correlation between lagged values and the most recent R&D figure. The Griliches, Hausman and Hall[1986] study found this lag effect to be significant for one period and very weak on the order of 0.05 using a log model of lagged effects. This suggests that only the latest previous period R&D variable contributes to patenting activity along with the dominant contemporaneous R&D variable figure. Thus we now develop a slightly more complicated evolutionary chain of R&D

expenditures to patent counts as output.

R&D--->	New knowledge --->	Propensity-->	-->	# patents
firm	Innovative R&D	to patent		variable
size	Present & R&D(1)	of firm		of patenting

The use of a correct functional form is also at issue. The log-linear transformations for both the R&D and patent variables has been taken as the basis for the econometric analysis that will be performed in the following three chapters. The existing empirical work regarding the relationship[see Griliches, Hall and Hausman 1986 and Pakes 1984] has used this transformation. However the existing research has not substantively proved that this is the correct functional form. Thus, this thesis will use the nonparametric analysis to challenge the log-linear functional form. A better fit with the nonparametric model will place doubt on the functional relationship.

The problems due to the high degree of noise in the relationship suggest that the R&D-patent link is not a simple one. Further research may result in a number of other variables also having to be accounted for. Many of these are difficult to quantify without obtaining confidential financial and policy information from the companies in the study and thus will not be analyzed in this paper. Some of these issues include problems with firm sizes, diversification, propensity to patent, patent disclosure and industry averages. Propensity to patent across industries will be accounted for in this study using a scientific industry related dummy variable analogous to the Griliches 1990 study. This is also comparable to the standard fixed effect model used by Pakes and Griliches[1985]. Their model though also accounted for the differences in the propensity to patent across firm subgroups.

In the next chapter the methodology related to the parametric and nonparametric models used will be discussed.

CHAPTER 2: PRELIMINARY DATA ANALYSIS: THE R&D-PATENT LINK

2.1 Data:

The patent data was obtained from the CD-ROM files of the US Patent and Trademark Office, an agency of the Department of Commerce which oversees the patent application process. The corporate patent counts used will be restricted to aggregate patents awarded to the firm during a one year period. Information regarding the applications for patents by companies was difficult to obtain. Thus these values and the patent application/success ratios were not used in this study.

Through the preservation, classification and dissemination of patent information, the office aids and encourages innovation. The functional role of the office is to examine the applications made, and grant patent rights to inventions where significant technological innovations have been made. The patent protection represents a property right that is given to the inventor by the government. The process may take from 12-18 months and research is therefore conducted after the initial application. The term of the patent is 17 years from the date the patent is granted, subject to the payment of annual maintenance fees. The right conferred by the patent grant is "the right to exclude others from making, using, or selling the invention."

In the language used by the statute, the patent can be granted to any individual who "invents or discovers any new and useful process, machine, manufacture, or composition of matter, or any new and useful improvements thereof, may obtain a patent." Thus any industrial or technical process that is considered a significant improvement over the existing ones maybe patented. The term 'manufacture' refers to articles which are made, and also includes all manufactured articles. The term 'composition of matter' refers to chemical compositions and may include mixtures of ingredients as well as new chemical compounds. The subject matter must also be sufficiently different from what has been used or described before so that it may be said to be unobvious to a person having ordinary skill in the area of technology related to the invention.

The dataset consists of 13 years of annual patent counts, beginning in 1977; this is slightly larger than the dataset considered in Griliches and Pakes (1990). The 1989 cutoff year was necessary because of the matching data required from Compustat's finance files; at present, these are only updated until this period.

In order to incorporate industry-specific effects in the analysis, data on publicly traded firms from Compustat was combined with the patent dataset. It is important to note that using Compustat files restricts the sample to companies trading on the AMEX and NYSE stock exchanges, and this may bias results to the extent that small firms are under-represented in the combined sample. Table 4.1 provides some indication of the size distribution of firms in the sample.

TABLE 2.1 DISTRIBUTION OF ASSET SIZES OF FIRMS

Asset Size	# Firms
1M<	6
1-10M	18
10-100M	36
<100M	29

The companies were grouped into industry categories to compensate for the propensity to patent differences across industrial sectors. The industry groups do not follow SIC coding which is the traditional basis for separation. Rather it is based on the Value Line Investment Survey's industry groupings. Each industry has between 7-12 companies per group. There is a relatively broad spectrum of industries included in the study. Dummy coding was introduced to differentiate between high technology and low technology firms. Since this is a relatively small firm sample to identify with dummy codings, only two categories were created.

TABLE 2.2 BREAKUP OF DUMMY CODING

DUMMY CODE=1	DUMMY CODE=0
INDUSTRY	**INDUSTRY**
Paper Products	Car Parts
Precision Instrument	Tire & Rubber
Chemical	Consumer Products
Electronics	Diversified Industry
Electric	Medical Prods & Services
Automobile	Container/Packaging
Defense	Steel (Integrated)
Conglomerates	

Thus firms in scientific sectors where substantial patenting is conducted were separated from low patent groups. Similar industry groupings were used by Griliches[1986].

These dummy codes are defined in the results tables under the pseudonym **Scidum**. This fixed effect will allow for the predominantly high-technology scientific industries to be defined as a '1' and a '0' coding for non-scientific industries.

2.2 Financial Profile:

It is also useful to consider some of the financial characteristics of the firms in the combined dataset. Table 4.3 contains information on a variety of standard performance ratios used in financial analysis, with above-median patent performers grouped in a "high-patent" group, while below median patent performers placed in a "low-patent" group. The table contains information on average financial ratios within groups, and also presents standard t-tests for the difference in means between groups. The following variables were compared between the two groups.

1. **Asset value:** The asset value of the firm is used
2. **Sales:** This represents the net sales of the firm
3. **NOI/sales:** This is a **performance** ratio describing the firm's operating income before extraordinary items. It is then weighted by the sales figure to give it a relative value.
4. **CF/assets:** This is also a **performance** figure. This time the cash flows of the firm are defined as; net income plus depreciating plus any adjustments for all

accrual and deferrals.

5. **Sales/assets:** This is another standard descriptor of this type of profile. The statistic describes the **performance** of the firm. The value though does not have the intuitive value of #3 and #4.

6. **Working capital/assets:** This is a **liquidity** ratio defining the firm's ability to meet present operating obligations. The ratio is the cash(or equivalent ie. stocks, bonds) plus accounts receivable plus inventories plus prepaid expenses.

7. **FLEV(1):** This is a **liquidity** ratio defining the capital structure of the firm. It is defined as the long-term debt/market value of equity(shareholder's equity).

8 **Equity/debt:** Defined as **Owners' equity/creditor's equity.** This will offer a substantial amount of information considering the firm's ability to finance capital spending projets with debt rather than equity. A high ratio would mean such a case. A more straightforward **liquidity** ratio. While the FLEV figure is more important for financing of major projects and capital investments, this is the more common ratio used by rating agencies. It is total equity/debt.

9. **R&D/assets:** This figure represents the firm's relative research and development expenditures.

The comparative assessment should project the differences that are relevant between the two samples. From this preliminary analysis there can be an assessment of the difficult financing decisions available. All units are in millions.

The most striking evidence from the table is the significant difference between average R&D/assets for high and low patent firms; it appears that high patent firms perform significantly more R&D, which is the first indication of support for the first hypothesis. There are some other marginally significant differences, but it is not clear that controlling for these differences would have an appreciable

TABLE 2.3 FINANCIAL PROFILE

Description	Low Patent Mean (Std dev)	High Patent Mean (Std Dev)	In means t-difference
1. Asset size(in M)	1888.98 (2048.98)	1495.50 (2029.58)	-2.630*
2. Sales(M)	2094.42 (2098.27)	1604.09 (1941.48)	3.230*
3. NOI/sales	0.0054933 (0.0307436)	0.0054567 (0.0334587)	0.01578
4. CF/sales	0.1703656 (0.0754264)	0.1622841 (0.0745430)	1.508
5. Sales/assets	1.3282854 (0.3740479)	1.3778126 (0.2881896)	2.082*
6. WC/assets	0.1806185 (0.0722744)	0.1798354 (0.0737314)	0.153
7. FLEV	0.4964444 (0.1379215)	0.4770036 (0.1261063)	-2.050*
8. Equity/debt	1.4056799 (0.5429690)	1.2809423 (0.7924929)	2.878*
9. R&D/asset	0.4850364 (0.1657230)	0.5744528 (0.1195828)	8.640*

* Statistically significant at 0.05 level

effect on the results presented in Chapter 4. Of course, one should generally be cautious in interpreting these test statistics, as they only have asymptotic justification under fairly strict assumptions.

2.3 Visual Analysis:

Figure 2.1 shows the relationship between relative R&D and asset size for the panel of firms in the dataset. It

FIGURE 2.1:

R&D VERSUS SIZE

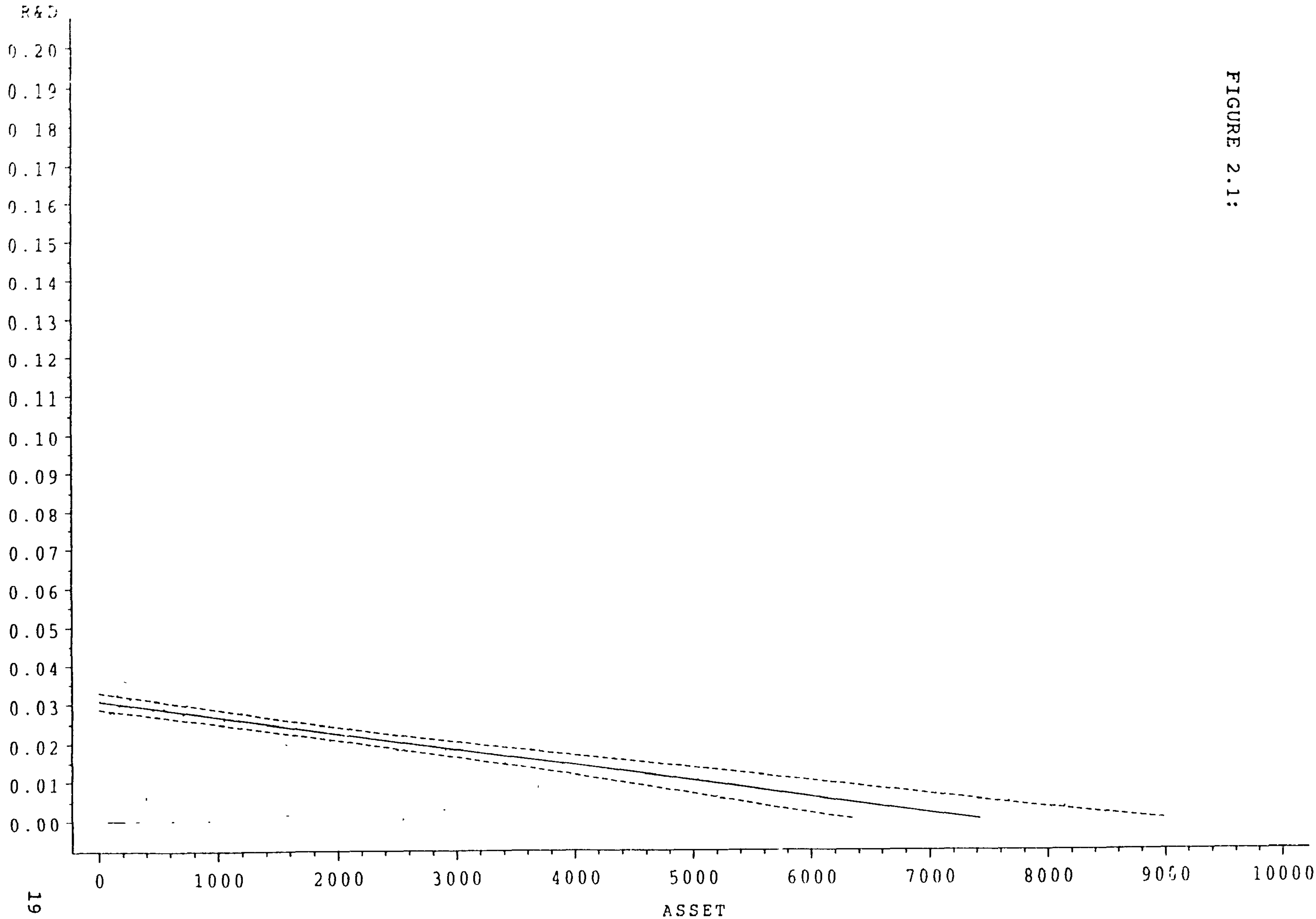


FIGURE 2.2:

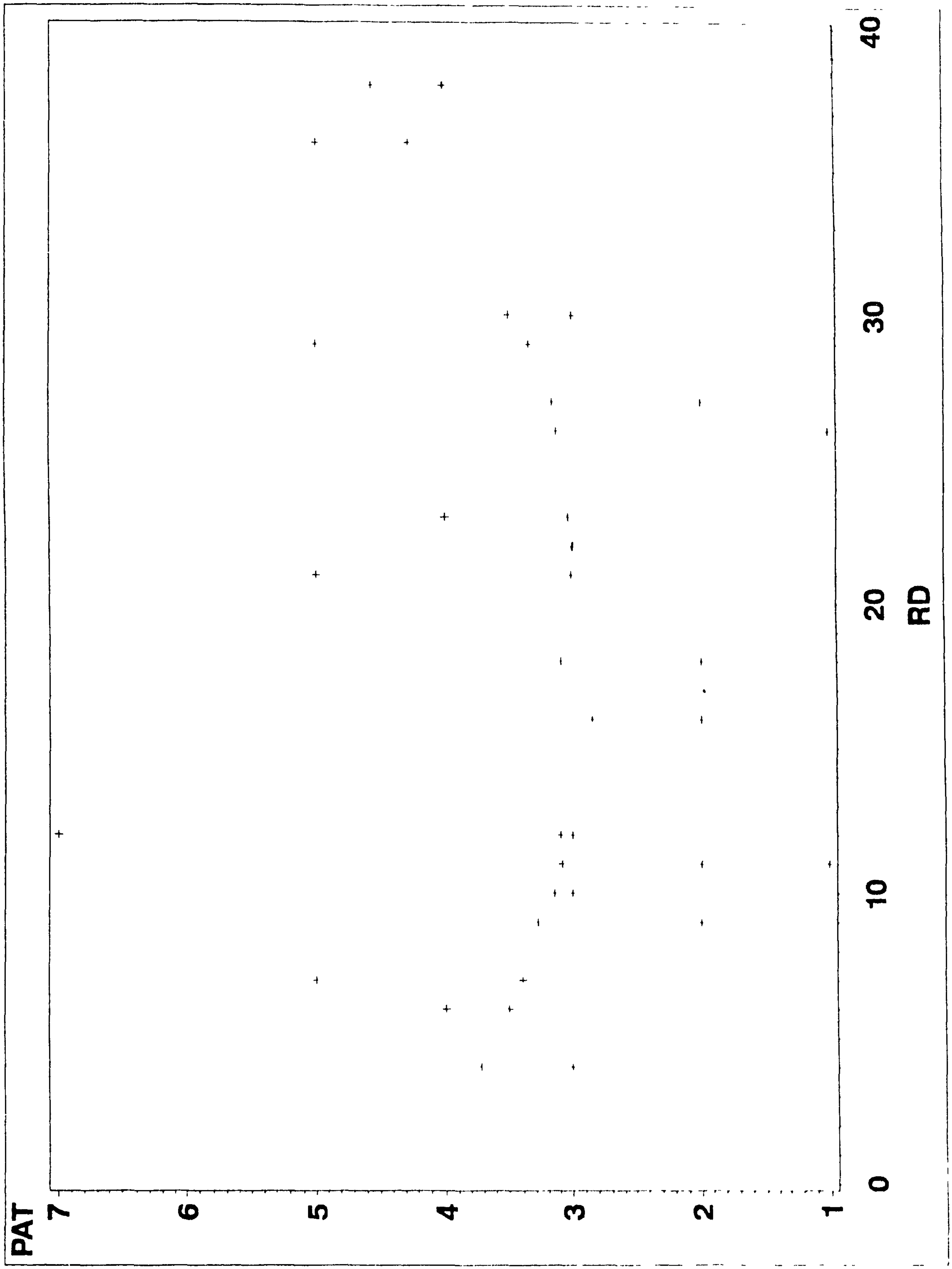
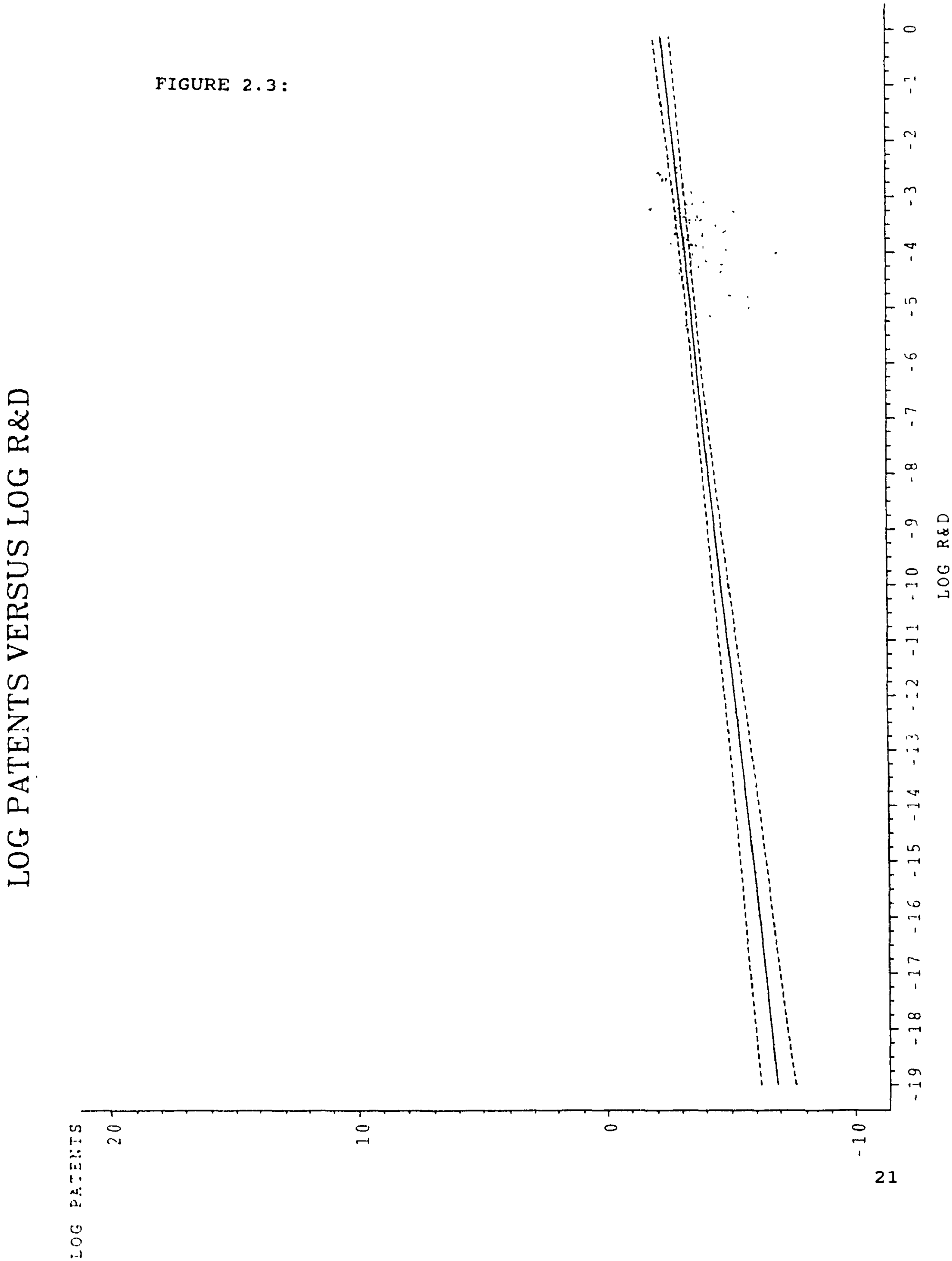


FIGURE 2.3:


LOG PATENTS VERSUS LOG R&D
LOG PATENTS
20
10
0
-10
LOG R&D
0
-1
-2
-3
-4
-5
-6
-7
-8
-9
-10
-11
-12
-13
-14
-15
-16
-17
-18
-19

appear that relative corporate R&D spending exhibits an inverse relationship with asset size as discussed earlier. The trend line shows a concave decreasing function with a slight spike in the trend among mid-sized firms, indicating that firms are investing a greater portion of their asset value in R&D during the early phases of their life cycle. This seems to support the argument of Mansfield [1984], in which larger organizations with larger infrastructure or being more established may not need to pursue innovation to the extent that lesser firms do.

The graph of patents vs R&D does not exhibit a clear relationship. (See figure 2.2). The wide distribution of the scatter points do not have any particular pattern. The existing theory by Pakes [1984] and other authors have chronicled the relationship as being log-linear in nature; Figure 2.3 uses the log specification of patents(lptwei) vs. log R&D(lrdwei). We now have a more linear pattern of observations. The slightly upward slope is relatively consistent with no major outlying observations.

CHAPTER 3: ECONOMETRIC METHODOLOGY

3.1 Parametric Methodology:

Previous studies contain a listing of the correlations between the 3 variables, and it is evident that the contemporaneous R&D variable is the most strongly related to the log patent variable. This is consistent with the theory that the contribution of older R&D investment becomes less valuable as time passes. [Hall, Griliches, and Hausman 1986].

Based on the existing theory, (Griliches[1990] and Hall, Griliches, and Hausman [1986]), the log-linear transformation will be used for R&D and patents.[1] The initial analysis will investigate the relationship between research and development expenditures and the patent variable, and will also investigate lagged R&D. For the empirical work, the dependent variable will be log(patents/assets)=lptwei or Log P in the tables, while the explanatory variables will be current and lagged values of log(R&D/assets)=lrdwei or LogR, i.e.[1]

Equation 3.1 $\quad lptwei = B_0 + B_1 * lrdwei + error$

The first group of models that will be investigated are parametric in nature, and differ primarily with respect to the assumptions on the error term in the above equation. Table 3.1

[1]The Box-Cox transformation procedure was used to confirm the log-linearity in the relationship between R&D and patents. This transformation had the highest R^2 value.

presents standard OLS estimates, where each panel is stacked and individual firm-specific fixed effects are included to absorb the variance due to differences in propensity to patent across firms. This preliminary specification is advantageous in that the estimates to be consistent under fairly general conditions. The second model consists of a series of maximum likelihood estimates which are non-linear least square estimates. These employ a Gauss-Marquardt algorithm to minimize the sum of squares and maximize the log likelihood respectively. For this version of the model we are unable to obtain conditional estimates, due to its intrinsic nonlinearity and the shortness of our panel.

For the third and fourth models, we assume that the disturbance follows a Poisson or negative binomial distribution. This follows a similar procedure used by Griliches, Hausman and Hall[1988]. For these estimates we are able to obtain robust standard errors which are correct in the presence of arbitrary heteroscedasticity including year to year correlation within firms.

The Poisson model assumes that the variance of the disturbances are proportional to the expected value of the patents and weighs the observations accordingly. The Poisson distribution is often a reasonable description for events which occur both randomly and independently in time. It is a natural first assumption for many counting problems in econometrics. Denoting the Poisson parameter as Lambda(Y), we will consider specifications of the form logY=XB where X is a vector of regressors which describe the characteristics of an observation unit in a given time period *t*.

The Poisson specification allows for convenient time aggregation so long as its basic assumption of time independence holds true. The time independence property is also a potential weakness of our specification given the often noted serial correlation of residuals in econometric specifications. The basic Poisson probability specifications is:

Equation 3.2 $pr(n_{it}) = f(n_{it}) = \frac{e^{-Y_{it}} Y_{it}^{n_{it}}}{n_{it}!}$

The Y_{it} is a deterministic function of X_{it} and the randomness in the model comes from the Poisson specification for the n_{it}. The moment generating function of the Poisson distribution is $m(t)=e^{-Y}e^{Yt}$ so that the first two moments are $E(n_{it})=Y_{it}$ and $V(n_{it})=Y_{it}$. The regression property of this specification arises from $E(n_{it})=Y_{it}$ but it is not uncommon to find that the variance of n_{it} is larger than the mean empirically, implying overdispersion in the data. The log likelihood of a sample of N firms over T time periods for this Poisson specification is found below.

Equation 3.3:

The Poisson specification is similar to the familiar

$$\log L=\sum_{i=1}^{N}\sum_{t=1}^{T}[y_{it}!-e^{X_{it}B}+y_{it}X_{it}\beta]$$

econometric regression specification, but is superior in that it specifically recognizes the discrete "count" nature of the data.

The parameters in the Poisson model are estimated by maximum-likelihood. As the log-likelihood function is globally concave, maximization routines converge rapidly. Even with the fixed effects Poisson model, we still have the restriction that the variance and mean are equal, $En_{it} = V(n_{it}) = Y_{it}$. On the other hand, the random effects Poisson has a variance to mean ratio of $1+Y_{it}$/gamma which increases with Y_{it} as our data indicates holds true. We would thus like to be able to combine the two models to permit the variance to grow with the mean. Using the negative binomial model of Hausman, Hall and Griliches[1984] we assume that the Poisson parameter Y_{it} is distributed in the population randomly and follows a gamma distribution. The negative binomial model generalizes the Poisson model by allowing for an additional source of variance above due to pure sampling error. Also, since our data is in panel form rather than a single cross-section, we can allow for the possibility of permanent unobserved firm effects as well as the possibility that these firm effects are correlated with R&D and other explanatory variables. With the Poisson parameter Y_{it} following a gamma distribution with parameters(y,gamma), and y=$e^{X_{it}\beta}$ and gamma common across firms and time, the log-likelihood function for the model is:

Equation 3.4:

$$\log L=\sum_{i=1}^{N}\sum_{t=1}^{T}\log\Gamma(\lambda_{it}+y_{it})-\log\Gamma(\lambda it)-\log\Gamma(y_{it}+1)$$

$$+\lambda_{it}\log(\delta)-(\lambda_{it}+y_{it})\log(1+\delta)$$

Tables in chapter 4 will present the results from the parametric econometric analysis for the OLS, NLS, Poisson, and Negative Binomial models.

3.2 Nonparametric Methodology(LWR):

As theory provides very little precise guidance as to shape of the relationship between patents and R&D, nonparametric procedures provide an important and potentially useful means of examining regression relationships without imposing restrictive auxiliary assumptions (like linearity). In this section, nonparametric estimates of the regression function (the conditional mean) are presented. In the next section, the parametric models are compared with the nonparametric procedure in terms of out-of-sample forecasting performance.

The nonparametric estimation procedure employed here is an extension of the nearest neighbour approach called local weighted regression(LWR). The procedure was pioneered by Bruce Cleveland[1979] and has been subsequently refined and used by a number of authors including Cleveland and Devlin[1988] and Diebold and Nason[1990].

Local weighted regression(LWR) is a procedure for fitting a regression surface to data through multivariate smoothing. The local-fitting methods are analogous to the nearest neighbour methods but are dependant on distance weights for their estimates.

The purpose of LWR in this research thesis is to provide descriptive insight into the relationship between R&D and patents, to evaluate the performance of parametric models, and to provide guidance into further parametric specification. Since the estimates are locally calculated, this will be useful in modelling any non-linear trends in the data.

The estimation is concerned with nonparametric estimation of conditional means ie.

Equation 3.5:

$$E(y/x)=\int[yf(y/x)\,dy$$

Equation 3.6 $y_t=g(y_{t-1},\ldots,y_{t-p}) + e_t$

The LWR technique estimates g(x) at an arbitrary set of equally spaced $x=x^{*1}$, x^{*2}, $x^{*3}\ldots x^{*n}$ values. The estimates are based on p dimensional Euclidean distances via a weight function in:

Equation 3.7:

$$g(x^{*}) = \sum_{t=1}^{T} w_{kt}(x_t)\, y_t$$

Where $w_{kt}(x_t)=1/k_t$ is the weight function. K_t represents the k_t nearest neighbour of x^*. Thus LWR fits the surface at a point x^* as a function of the y values corresponding to the k_t nearest neighbours of x^*.

The estimation procedure requires the specification of a smoothing parameter, as do all other nonparametric regression procedures. The smoothing constant is a value between 0 and 1 and affects the regression estimates by the relationship $2k_t$=int(eida*T), where the eida determines the number of nearest neighbours used and hence the degree of smoothing. The x_t distances are ranked from the predetermined x^* value creating a series of distance functions lambda. Thus the Euclidean distance function is as follows:

Equation 3.8

$$\lambda(x^{*}, x_{kt}^{*} = [\sum_{j=1}^{P} (x_{ktj}^{*} - x_j^{*})^2]^{.5}$$

We are then able to form a neighbourhood weight function.

Equation 3.9:

$$v_t(x_t, x^*, x_{kt}^*) = C[\lambda(x_t, x^*)/\lambda(x^*, x_{kt}^*)]$$

In this case C is the tricube function which is an arbitrary weighting function used by Cleveland and Devlin[1988] and Diebold and Nason[1990]. The justification for the tricube weight function is that it produces a smooth, gradual decline in weight with distance form x^*.

Results of the LWR procedure are documented in the section on nonparametric results in chapter 4. Various smoothing parameter values were tested across the different lag structures used.

CHAPTER 4: THE R&D-PATENT RESULTS

4.1 Parametric Results:

The parametric estimation procedures are consistent with the specificity of the log-linear model. The initial results in table 4.1 are OLS parameter estimates. The fixed effect scientific industry dummy variable was found to be not significant and therefore not entered in the table. Thus, the remainder of the model building is described in the segmented form below:

TABLE 4.1 REGRESSION ESTIMATES OF LOG PATENTS

EQUATION	(1)	2)	(3)
Log R_t	0.29869 (0.0001)	0.217249 (0.0001)	0.211706 (0.0001)
Log R_{t1}		0.085692 (0.0100)	0.048341 (0.2455)
Log R_{t2}			0.049663 (0.1362)
R^2	0.1767	0.1827	0.1842

* not significant

The estimates suggest a significant relationship exists between the contemporaneous and 1st lag R&D values only. The addition of the second lag is inconclusive. The highest estimates are for the contemporaneous values. We have a value of 0.29869 for the contemporaneous R&D coefficient. The subsequent lagged values exhibit lesser values and are significant only until the 1st order lag structure.

The durbin-watson test statistic is 2.082. This confirms that no significant autocorrelation exists. However since panel data as opposed to time-series data are being used, we do not attach importance to this value. In an attempt to be consistent with the previous tests of Griliches, we will subsequently estimate the models using different distribution specifications for the error term. Initially though, the following table has ML regression estimates of log patents vs. log R&D:

TABLE 4.2 ESTIMATES OF LOG PATENTS USING MAXIMUM LIKELIHOOD

EQUATION	(1)	(2)
Log R_t	0.18181 (0.0001)	0.18652 (0.0001)
Log R_{t-1}		0.09133 (0.0604)
Log R_{t-2}		
Regression R^2	0.0924	0.0974
Total R^2	0.8319	0.8284

Note - Scientific dummy variable and interaction term was not significant in any of the above models.

The relationships is consistent with OLS estimates in that a positive relationship exists between research and development and the patent variable. The most significant relationship is between the contemporaneous R&D and the patent variable. Subsequent lags show a rapid reduction in their predictive nature. In addition, beyond the first lag R&D variable, the p values rise sharply. This infers that either there is excessive autocorrelation resulting in a loss of information, or only the first two are significant. Since Griliches[1990] also found the autocorrelation estimates to be quite high, he concluded that it was difficult to distinguish the contribution of the lags to the dependant patent variable.

In table 4.3, a summary is presented of the selected models using the procedures available. The Poisson and negative binomial procedures gave a model that produced similar estimates obtained from the regression and autoregressive procedures.[1]

TABLE 4.3 SELECTED MODEL

EQUATION	**OLS**	**NLS**	**POISSON**	**NEGBIN**
Log R_t	0.14726 (0.0001)	0.13875 (0.0001)	0.17634	0.14532
Log R_{t-1}	-0.11185 (0.0001)	-0.11473 (0.0001)	0.02134	0.02253
Regression R^2	0.8574	0.9221	n.a.	n.a.
Total R^2	0.8574	0.8637	n.a.	n.a.
MSE Criterion	0.9561	0.9154	0.24957	0.27943

The regression model is with the highest R^2 value of 0.9221 using the AR non-linear least squares process. The last two models displayed significantly lower MSE values than the initial two. This suggests that specifying the Poisson and negative binomial distributions improves the predictive nature of the model. The existing research in this area corroborates the results that Poisson and negative binomial distributions produce lower MSEs.

[1]Forward, Backward, and Stepwise selection procedures were used to validate the models that were significant.

4.2 Nonparametric Results:

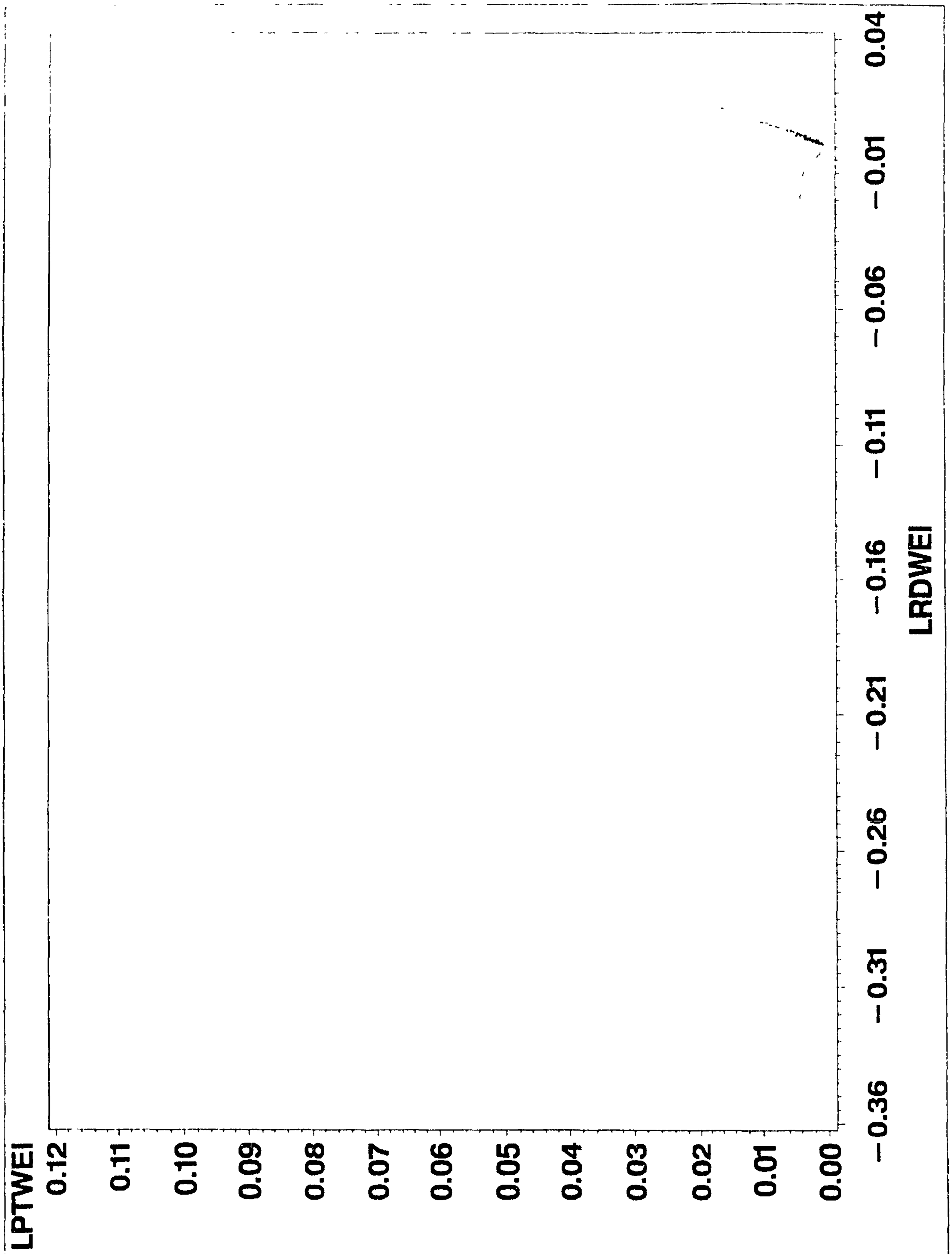
The sample size for the LWR estimation was 672 observations after the deletion of missing values. The LWR estimation values are based on the mean square prediction error(MSPE) and mean adjusted prediction error(MAPE) criterion. The out of sample analysis was based on splitting the sample into 2 sections. The main sample was 600 observations, with 72 observations being segregated from the rest using time as a criteria. Prediction errors were calculated on the 72 subset of observations.

The depiction of the smoothing parameters in Figure 4.1 shows a plot that exhibits two distinct functional trends. The first section trends downwards until a minimum value after which the graph moves towards higher R&D values by a rapidly increasing slope. This first graph represents robust estimates of the regression parameters.

The subsequent graphs in Figures 4.2-4 depicts the plots representing each of the smoothing parameters. This graph is the one dimensional depiction of the R&D-patent relationship. The contemporaneous R&D plot was graphed with the 0.1, 0.4, 0.7, 1.0 parameters over the range of data. The movement of the plots varies with the 0.1 parameter resembling the robust LWR estimation of Figure 4.1 the closest.

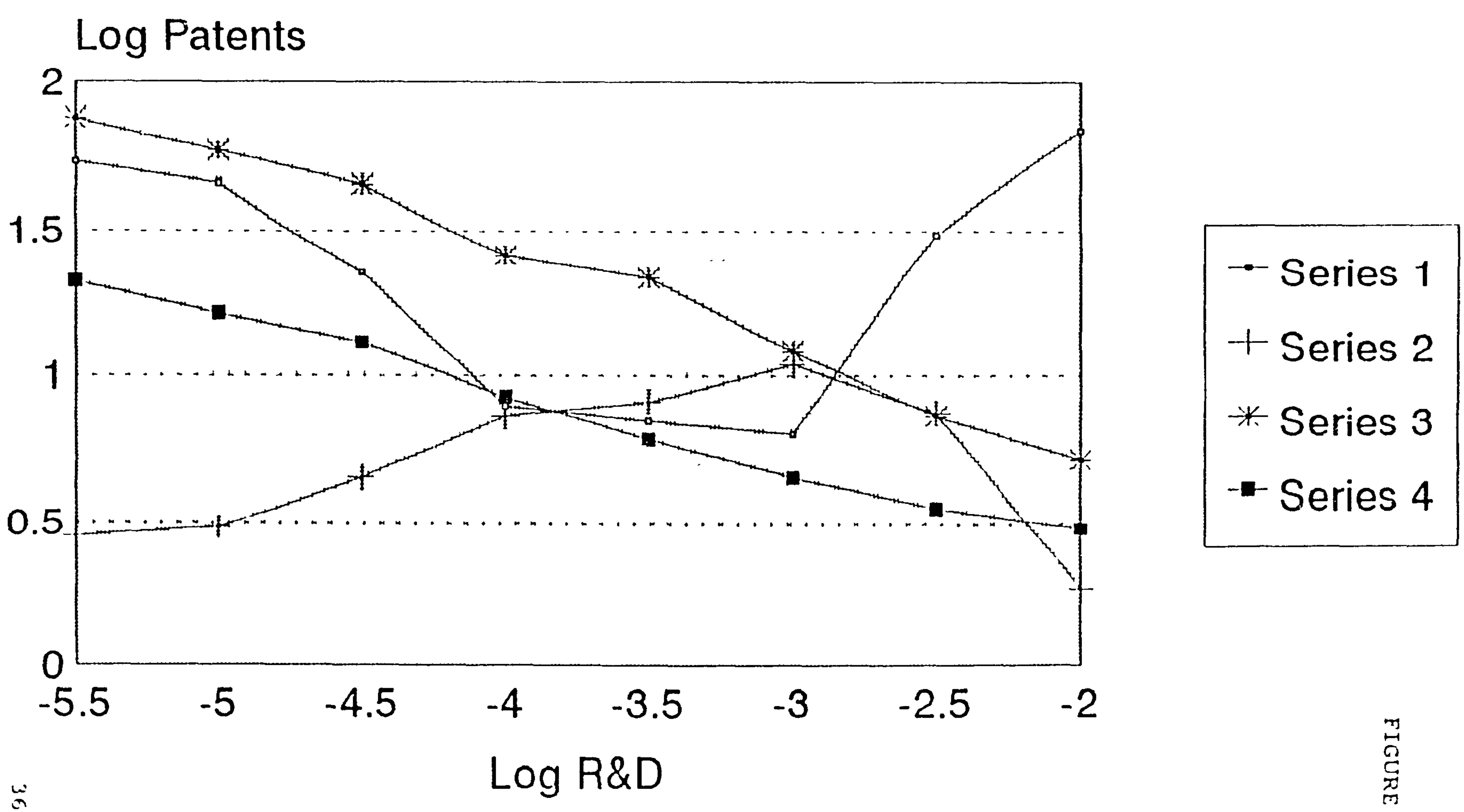
For the 2 dimensional visual analysis(Figure 4.3 and 4.4), we introduce the first lag of R&D which was found to be significant in the parametric analysis(see later on). In this

FIGURE 4.1:


LPTWEI
0.12
0.11
0.10
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0.00
LRDWEI
−0.36
−0.31
−0.26
−0.21
−0.16
−0.11
−0.06
−0.01
0.04

Log Patents vs. Log R&D

Local Weighted Regression(LWR)



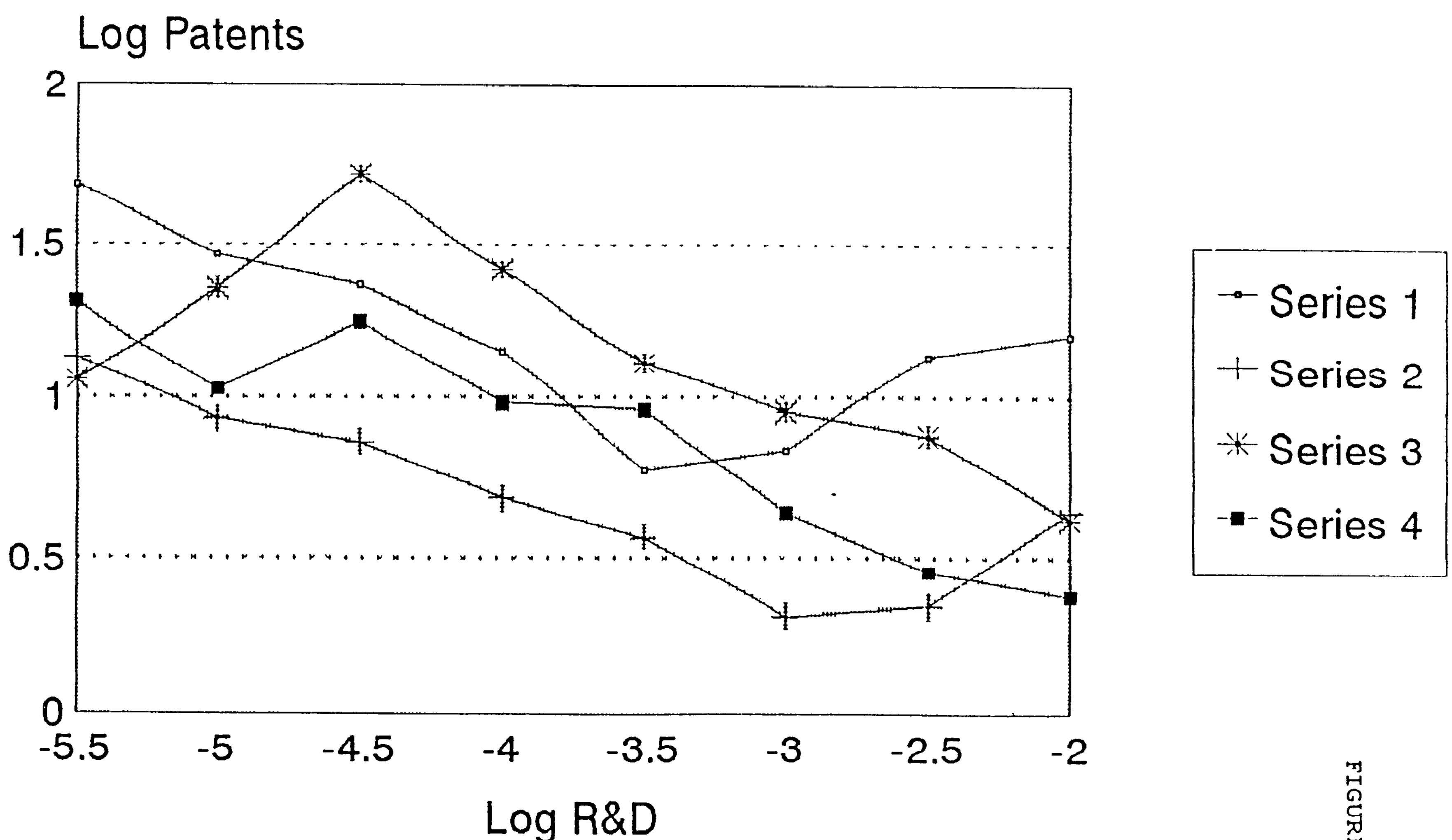
Smoothing Parameters Series 1-4: 0.1, 0.4, 0.7, 1.0

FIGURE 4.2

FIGURE 4.3:

Log Patents vs. Log R&D 2 Dimensions

LWR Holding Contemporaneous R&D Constant

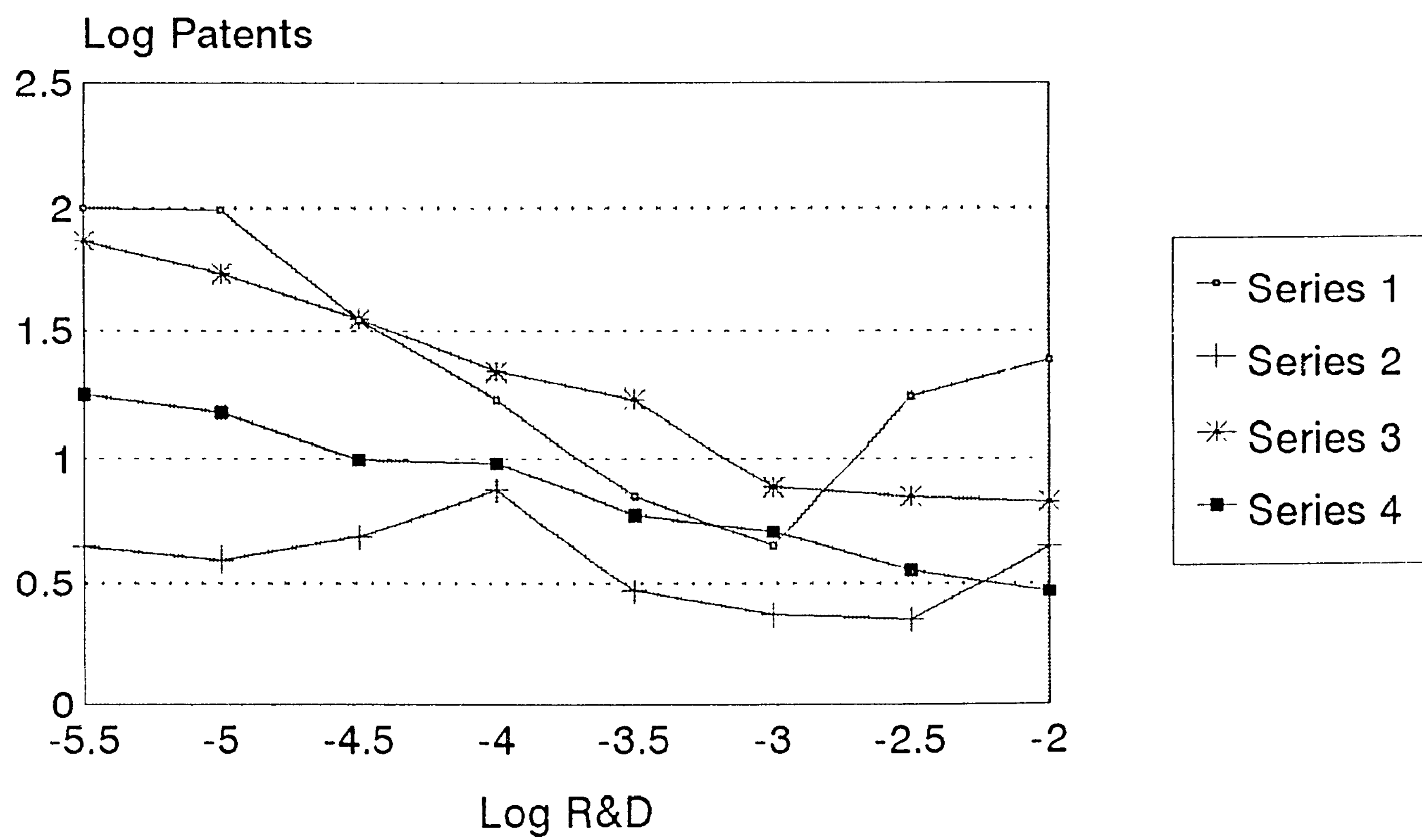


Smoothing Parameters Series 1-4: 0.1, 0.4, 0.7, 1.0

FIGURE 4.4:

Log Patents vs. Log R&D 2 Dimensions

LWR Holding 1st Lag R&D Constant



Smoothing Parameters Series 1-4: 0.1, 0.4, 0.7, 1.0

case, there are two graphs; one of them holding the contemporaneous R&D value constant. The second holding the lagged R&D value constant and plotting the contemporaneous value. In both cases we have the different smoothing parameter(Sp) plots exhibiting different estimates over the R&D-patent regression space. The 0.1 Sp exhibits the closest semblance to the first two figures.

The sensitivity analysis results in an in-sample set of values listed in the following four tables. These provide values for a range of 4 different smoothing parameters. The in-sample results were found to have values that were fluctuating between them. Thus the model we are analyzing is the following:

Equation 4.1 Log Patents = Log R&D + e

TABLE 4.5: IN SAMPLE ANALYSIS OF PATENTS

SMOOTHING	P=1		P=2	
PARAMETER	MSPE	MAPE	MSPE	MAPE
0.1	0.48211	0.51352	0.53765	0.51785
0.4	0.47231	0.49314	0.53697	0.50721
0.7	0.44217	0.44797	0.53675	0.50698
1.0	0.38194	0.41093	0.53645	0.48669

For p=1 we have a contemporaneous examination of the relationship between the two values. Therefore, there is an existing bias towards the optimal values. These are generated mostly near the 1.0 value of the smoothing parameter.

Equation 4.2:

$$\text{Log } P = \text{Log } R_t + \text{Log } R_{t-1} + \log R_{t-2} + e$$

The regression equations are analogous to the p=1 and p=2 tables above. The out of sample forecasts are documented in the final section on contrasts.

Comparison of Parametric vs. Nonparametric Models:

Using the patent flow out-of sample results from the parametric and nonparametric estimations, the MAPE values are lower with the nonparametric models when compared with the OLS and NLS models from subsequent sections. The nonparametric values hover in the 0.42 range for p=1 and 0.31 for p=2. Whereas the parametric models are 0.6843 and 0.7214 respectively for OLS and NLS procedures.

TABLE 4.6: OUT OF SAMPLE FORECASTS

Smoothing Parameter	P=1	P=1	P=2	P=2
	MSPE	MAPE	MSPE	MAPE
0.1	0.4276	0.4278	0.3589	0.3804
0.4	0.4270	0.4272	0.3482	0.3579
0.7	0.4168	0.4170	0.3362	0.3648
1.0	0.4165	0.4167	0.3249	0.3112
Parametric Results MAPE	OLS 0.6843	NLS 0.7214	Poisson 0.3574	Neg binom 0.2613

This suggests that some further specification maybe necessary to improve the parametric estimation. Another possible problem with the out of sample prediction of the patent variable are the non-linear trends in the nonparametric log patent vs. log R&D graph. Since the LWR procedure is locally regressed, there is more flexibility in estimating curvilinear trends in the data set.

The Poisson model and the negative binomial model had MAPEs that were comparable to the parametric results. This suggests that these two versions of the model were correctly specified. The forecast errors of the Poisson model are approximately one-half of the errors exhibited. The negative binomial model has one-third the errors of the OLS and NLS models and slightly less than the Poisson model. Thus it can be argued that the properly specified parametric models with the Poisson and negative binomial specifications can be accurately established. The out of sample analysis is based on sample breakup with the estimates of the in sample used as predictors of the out of sample data.

The subsequent plots represent the p=2 values for different smoothing parameters. These 2 plots describe a more linear relationship.

4.4 Concluding Remarks:

A residual analysis for the last two models was performed on the OLS model above.[1] Since the significant outlying

[1]An attempt was made to evaluate any outlying observations through a residual analysis. Since the outliers represented less than 1% of all observations, they were

observations represented less than 1% of all the observations, there was no attempt to remove these observations from the sample data.

Due to time limitations certain research areas were not as vigorously pursued. This pertains to two areas. One of them is related to the constraints used by numerous authors such as Griliches[1990], Mansfield[1984] and Ben-Zion[1984] to attach constraints to the R&D expenditures.

Some of these constraints are firm-specificities which create differences in patenting activities. Other areas are related to the depth and breadth of patenting as well as the significance of these patents. Many patents are irrelevant and have little commercial value. Others are highly significant breakthroughs. A model incorporating these factors would surely improve our knowledge related to cash flows and the firm's R&D programs. In addition these have implications upon the specifications of the models we use.

The second area of research that can be pursued is related towards more closely identifying the econometric techniques that will maximize the model. This paper has simply attempted to offer an overview of techniques that can be applied to this area of research. A more narrow focus will eventually be more fruitful.

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left in the data.
The estimation used Cook's D, Student Residuals, Hat's Matrix and Dfitts procedures. In addition, Dbetas tests confirmed the significance of the coefficients.

CHAPTER 5: R&D EVENT STUDY ANALYSIS

The purpose of this section of the paper is to evaluate the external perception of innovative activities by capital markets, and to resolve the claims concerning the allegedly destructive role of capital markets towards innovative long-term corporate investments. As previously noted in chapter 2, the advantage of using a market based approach towards analyzing innovative activity is the lack of functional form required. The returns data can be evaluated independent of any specifications. A positive perception by capital markets will result mean that investments in innovative activities enhance firm value. The goal of this section of the thesis will be to evaluate these perceptions within the framework of the second and third hypotheses we developed(see chapter 2). The first area of analysis will be with regard to research and development announcements, while the second will consider new product announcements.

The importance of research and development has been discussed by numerous authors in both the academic and popular literature. It is often suggested that the key to the sustained growth and competitiveness of a corporation rests with its commitment to continuous innovation. Therefore it is in the interest of the company and its shareholders to invest in long-term corporate research and development programs. These will maintain the corporation's competitiveness and result in greater profitability. Jensen[1986] made the point that there is little evidence to support the myopic market hypothesis put forth by some authors ie. Abernathy, Hayes, Hall etc. The decline of competitiveness in the United States, according to Jensen[1989] is related to management's myopic assumptions rather than those of the market. If markets are truly not myopic as Jensen claims, then research and development and new product announcements should result in a positive valuation of the market value of the firm. On the other hand, significant R&D expenditures have the potential to reduce the short-term profitability of the firm. Thus, rather than committing ourselves to any particular view, we will examine the evidence and by taking subsamples of our data, and attempt to understand the market effect of R&D announcements. This chapter begins with a brief discussion of event study methodology and then proceeds with the analysis of R&D announcements.

Event Study Methodology:

This study uses the event-study methodology pioneered by Fama, Fisher, Jensen, and Roll (1968) and refined by a large number of authors over the last two decades. For a recent survey of event-study techniques, see Brown and Warner [1985]. The initial assumption is underlying the procedure is that market model for the return generating process is well specified. In this instance, event tests are based on a group of statistics calculated using abnormal returns (referred to as prediction errors PE), where:

$$\text{Equation 5.1} \qquad PE_{it} = R_{it} - (A_i + B_i R_{mt})$$

In this situation, R_{it} is the rate of return on security i for event day t and R_{mt} is the rate of return on the CRSP equally-weighted index over the same date, A_i and B_i are coefficients which are typically estimated using the Ordinary Least Squares over an estimation period that begins 60 days prior to the announcement data and terminates 60 days ex poste. Examination of the prediction errors prior to the announcement but after the estimation period identifies information "leakage" prior to the announcement. For purely unanticipated announcements, examination of abnormal returns around announcement days provides evidence regarding capital markets perceptions of the announcements on firm value. As each return time series is normalized in "event-time", i.e. relative to the announcement date, cross-sectional aggregation of the abnormal returns provides a basis for powerful test statistics as idiosyncratic noise in the return generating process will be averaged out, leaving an accurate estimate of the average change in the name of the return generating process. One standard test statistic is the average prediction error. For each trading day within the event period, from 60 days prior to 60 days after, the average prediction error of the sample of n observations on each event day is calculated as:

$$\text{Equation 5.2} \qquad APE_t = 1/n \; PE_{it}$$

Under the null hypothesis of no abnormal performance, the standardized average prediction error has a standard normal distribution (asymptotically), i.e. for:

$$\text{Equation 5.3} \qquad z_t = SPE_{it}/n^{1/2}$$

a test of significance may be based on a standard two-tailed test using the normal distribution.

Nonparametric methods using the prediction errors provide an additional means for evaluating the null hypothesis of no abnormal performance that are robust to possible violations of the assumptions underlying the calculation of the asymptotic test statistic, including small sample sizes. The Wilcoxon sign rank procedure compares the number of negative abnormal return announcements(PEs) versus the number of positive ones; the test statistic of the sign test determines the significance level of the percentage of positive two-day returns during the announcement period is significantly different from the expected mean of 50%. This statistic is not affected by outlier returns, and serves as a check on the robustness of the difference of means tests[McConnell and Muscarella 1985]. The test statistic is computed as:

Equation 5.4 $z=(p-nr)/((n(1-r)r))^{5}$

where p is the number of positive two-day security returns during the announcement period, n is the total number of two-day security returns during the announcement period, and r represents the fraction of two day returns that are positive during the comparison period.

A complete analysis for changes in the value of the portfolio over time requires a cumulative abnormal return requirement. In our case this cumulative prediction error CPE takes into account the cumulative divergence of returns prior to and ex poste of the announcement date. This begins up to f(in our case=60) days before the announcement of the R&D or new product and ends 60 days after the date:

Equation 5.5:

$$CPE=\sum_{t=-f}^{f} APE_{1t}$$

In this event study analysis the CPE is calculated for the interval based on the publication date.

In general, this is the date the announcement appeared in the Wall Street Journal or other significant newspapers such as the Chicago Tribune. The announcement date is defined in the tables as day 0, and the prior day -1. There has been some discussion as to when capital markets incorporate the information of an announcement. Since we use the publication date as a proxy for when the information is actually released, the significant interval will be the day the announcement is printed and the prior day. The key interval is therefore the [-1,0] trading period in which the market will react most strongly to the news of the announcement and re-assess the share's market value. A positive or negative reaction that is statistically significant represents a notable reaction. This is the same procedure used by McConnell and Muscarella[1985], Woolridge[1987], and Chan et. al.[1990]. These returns will be documented in the event study tables listed following this section.

Data Collection:

The data was accumulated from Dialog Databases and Dow Jones News Services. The searches traced all relevant Wall Street Journal articles. In addition, in order to achieve a larger sample of announcements, I accessed more extensive sources. This meant including announcements from such diverse publications as the Chicago Tribune, Atlanta Herald, PR Newswire, Reuters etc. The final sample was just over 50% WSJ articles and a mixture of newswire announcements and local newspaper articles.

The announcements on newswires such as PR which accounted for about 6-9% of the sample were moved up one day since the effect was more likely to be well known the following day.

The rest of the sample were same day announcements. The event-time study accessed the CRSP(Centre for Research in Security Prices) data sets produced by the University of Chicago. The firms in the Chicago files were NYSE and AMEX companies. Thus, since our data set was limited to the 'big boards' ie. NYSE and American Stock Exchange companies, a certain size bias is implied.

The types of expenditure announcements in this study differ from the previous study analyzing R&D announcements by Chan[1991] in the sense that his announcements were the result of private corporate funding only. In this study there are R&D announcements that encompass government contracts, joint ventures, independent increases or decreases. In addition to examining the entire dataset, the analysis will also focus on 4 distinct subgroups of dataset. The 71 announcements were categorized in the following manner:

(1) R&D announcements showing increases in R&D spending as a dollar total.

(2) R&D announcements showing a decrease in R&D spending.

(3) R&D announcements describing investment in joint R&D ventures.

(4) R&D announcements describing the receipt of an R&D contract. This sample is weighted heavily towards government contracts.

The announcements were found in the databases using 'research and development' as search words, and groupings were established based on the information contained in the announcement. As examples, some of the announcements that were found are listed below:

(1) **Xerox** plans to boost 1986 research and development spending 8% from 1985 to almost $650 million.
Date: May 16, 1986 WSJ p. 31
Intel increasing capital, R&D spending.
Date: Jan 25, 1990 Reuters

(2) **Du Pont Co.** to cut its research and development budget for 1986.
Date: Feb 12, 1986 WSJ p. 34
Borg-Warner Corporation axes one-fifth of its corporate staff, slashes research, development staff by one-third
Date: Feb 17, 1987 Chicago Tribune p. 1

(3) **Digital, Cray** plan joint development of product to better link their lines. (Digital Equipment Corp., Cray Research Corp.)
Date: May 26, 1987 WSJ p. 4

The Liposome Company and Mitsubishi Kasei Corporation enter research and development agreement.
Date: Sept 23, 1988 PR Newswire

(4) **GE** units won Navy contracts totalling $108.9 million for research and development on nuclear propulsion and for FA-18 aircraft equipment.
Date: October 22, 1986 WSJ p. 54
ERC's research and development subsidiary wins $5.5 million cancer contract.
Date: Sept 27, 1989 PR Newswire

The sample was taken from a 6 year period 1986-1991. This time represented; a period of relative prosperity from 1986-89 and the commencement of a recession in 1990-91. The sample breakdown by year follows a relatively stable pattern except for the last two years. In the following table it is described. The year with the highest number of announcements was 1988. This may seem to be an opportune period since R&D spending during the recovery of the 1980s had resulted in

TABLE 5.1: FREQUENCY ANALYSIS OF ANNOUNCEMENTS

YEAR	FREQUENCY #	%	CUM. FREQ	CUM. %
1986	13	18.3	13	18.3
1987	9	12.7	22	31.0
1988	28	39.4	50	70.4
1989	15	21.1	65	91.5
1990	5	7.0	70	98.6
1991	1	1.4	71	100.0

substantial profits for most companies. The 1990 and 1991 figures suggest that firms were not making major research and development expenditures during the recession. This may be a cause for the low numbers. There is also some preliminary evidence [Chan 1990] that research and development expenditures are unfavourably perceived by the market after decreases in earnings. This may result in CEOs refraining from publishing their major R&D commitments during recessionary periods. Since the sample is based on research and development announcements which are less publicized than capital expenditure announcements, one would suspect that the sample is biased towards mainly larger firms. The distribution of firm sizes is categorized in the frequency table below. The results point to a relatively large asset size sample. The majority of the companies are firms with over 1 billion dollars in assets. This suggests that only the larger firms' research and development announcements

TABLE 5.2: FREQUENCY OF ASSET SIZES

ASSET SIZE	FREQUENCY	%	CUM FREQ	%
Asset< 20M*	4	5.6	4	5.6
20M<Asset<50M	2	2.8	6	8.4
50M<Asset<100M	6	8.5	12	16.9
100M<Asset<250M	2	2.8	14	19.7
250M<Asset<1000M	11	15.5	25	35.2
Asset>1000M	46	64.8	71	100.0

* Millions of dollars

are considered significant enough to be published. 15.5% of the sample came from mid-sized firms. The firms with assets under 250 million made up less than 20% of the overall group.

The event study analysis will focus initially on the total sample and then begin to portion the sample into the 4 'types' of R&D spending noted previously. The major difference between Chan et. al.[1990] was his elimination of R&D expenditure plans that involved funding from customers or from government contracts. Since we will analyze these individually later on, we have included them in the full sample. A last difference is that Chan et. al. eliminated concomitant announcements of R&D and decreases in capital spending by firms.

For the subsequent regression analysis the financial data for the companies was taken from the Compustat databases. This provided information on the asset size and R&D budgets of the prospective firms.

Full Sample Analysis:

The event-time studies used the abnormal returns criteria to assess the impact of the announcement. The share price's relative movement with regard to the market was assessed. The importance of this was alluded to earlier. The following is an analysis of the full sample of R&D announcements. Subsequent to this table will be an analysis of the critical 2 day period[-1,0]. The analysis will examine the abnormal returns over the days prior to and ex poste the announcement

TABLE 5.3: R&D ANNOUNCEMENTS FOR FULL SAMPLE

SUMMARY OF TWO-DAY [-1, 0] ABNORMAL RETURNS

Abnormal Return	-0.436
Z-value	-0.444
(p-value)	(0.6568)
Standardized Abn Return	-0.053
Day 0 Variance AR	4.861
Day 1 Variance AR	4.182
% negative	62.0
Wilcoxon Sign Rank p-value	(0.0210)
2-day standard deviation	3.204
# Observations	71

date. The two-day returns of the research and developments are not statistically significant at the 0.05 level. This value is noncommittal and the reason maybe suggested by the authors Chan et. al. [1990] with regard to the fact that earnings announcements prior to an R&D expenditure announcement may alter the market's perception of the investment. Since these earnings were not controlled for, this may account for the ambiguous results.

Another factor is that this sample was obtained from the Dialog Database. There are certain publications that do not have the national scope of the Wall Street Journal or the Dow Jones Newswire service as was mentioned earlier. This suggests that these 'smaller' announcements will have a more diffuse information impact, reducing their affect on the value of the stock.

Finally, the authors Chan, Martin and Kensinger also withdrew observations concerning multiple year commitments, contract funding and joint venture investments. They felt that such announcements incorporated certain elements that would bias their abnormal returns. Our analysis was based on maintaining our sample size and keeping external corporate and/or government funded R&D projects as a legitimate source of R&D activity. From the same perspective, joint R&D ventures are also, from my perspective, a legitimate and growing type of R&D financing for corporations.

R&D Announcements by 'Type':

In the following sections, we have broken the R&D sample into five groups. Independent event studies were conducted on all of these groups. Since the returns on the overall sample were not statistically significant, this will afford us an opportunity to compare the data within the groups. This comparative analysis will be more productive in terms of providing beneficial information concerning the market's evaluation of these announcements.

The negative reaction is quite pronounced in the frequency distribution of returns listed in the table above. The key difference was the -2%>AR>-4% reaction where 11 announcements were found. This supports the pronounced negative reaction of the sample. It also refutes the argument that a group of outlier negative AR observations are biasing the sample. As a reviewer in Chan's article pointed out, an R&D announcements in the face of negative earnings maybe perceived unfavourably. Thus to find the answers to these questions and to disseminate the types of R&D announcements, we must look further into the sample breakdown.

In Figure 5.1 we have the CAR data which examines the abnormal returns around the announcement date. The graph exhibits an upward surge 1 day before the announcement date. This suggests that the market has been leaking information and is already in the process of discounting the value of the firm. This ultimately generates a selloff at the [-1,0] interval resulting in a negative return. It also suggests that the market is not evaluating R&D announcements favourably.

FIGURE 5.1:

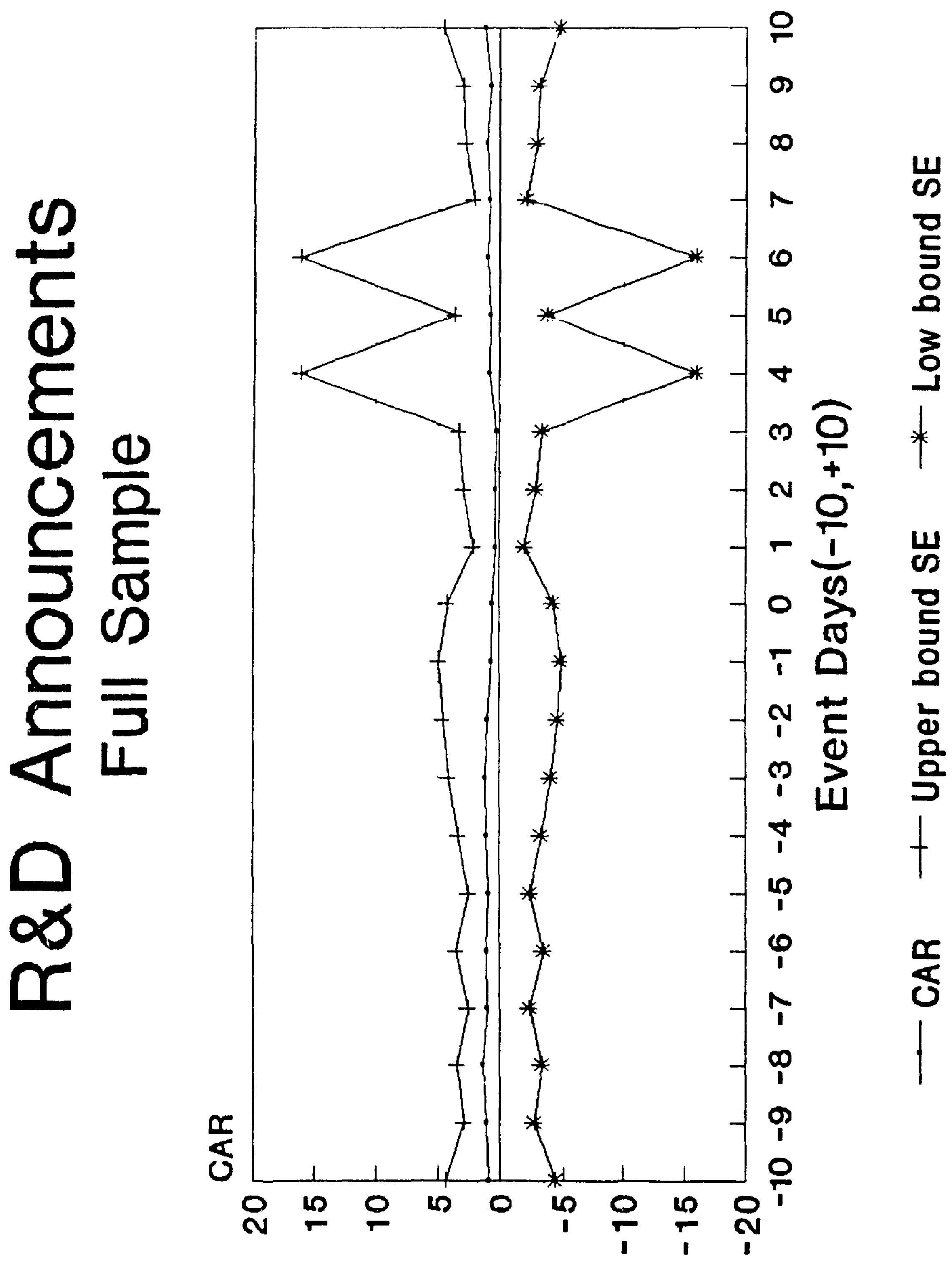

R&D Announcements
Full Sample
CAR
20 15 10 5 0 -5 -10 -15 -20
-10 -9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10
Event Days(-10,+10)
CAR
Upper bound SE
Low bound SE

TABLE 5.4: ANNOUNCEMENTS FOR INCREASES ONLY IN R&D BUDGETS

	SUMMARY OF TWO-DAY [-1, 0] ABNORMAL RETURNS
Abnormal Return	-0.123
Z-value	0.536
(p-value)	(0.5918)
Standardized Abn Return	0.066
Day 0 Variance AR	5.239
Day 1 Variance AR	4.127
% negative	56.7
Wilcoxon Sign Rank p-value	(0.2193)
2-day standard deviation	3.248
# observations	67

This event-time analysis was an attempt to validate the results of antecedent authors in the field. By removing the negative announcements(5) we were able to obtain results for 'positive' research and development decisions by firms. While the sample is still aggregated into joint ventures, contracts, and dollar value increases, it is now a sample that is focused exclusively on positive R&D events. The mode of this R&D funding maybe internal or external in nature.

The event-time study showed that once again we have an negative abnormal reaction of -0.123. This though is substantially lower than the -0.436 reaction that was found in the full sample. The standardized value shows a positive reaction of 0.066 is being generated. In the frequency table, the -2%>AR>-4% reaction interval has shrunk from 11 announcements in the full sample to 6 announcements. The nonparametric 56.7% negative value for the Wilcoxon sign rank test supports the negative bias. It should be noted that this value of the sign rank test, is not significant with a p-value of 0.2193. The next step will help us understand what forms of R&D announcements will be favoured from this sample. This will allow us to differentiate the types of R&D announcements.

Thus, the following sections will attempt to determine whether one 'type' of research and development reaction is responsible for a relatively larger share of the positive or negative reactions. The results though are subject to a relatively small sample size.

Thus, the next set of announcements are the most comparable to those used by Chan et. al.[1990]. They represent 'dollar' value increases in research and development announcements. While Chan et. al. threw out R&D announcements that were simultaneous with capital expenditure reactions, the sample is reasonably similar. It should be noted that multiple year R&D commitments were retained. These were considered notable since they defined a long- term plan for the company's research program.

From a relative analysis, the negative reaction was not as large as the -0.436 of the overall sample and the -0.123 of the sample of positive announcements only. The p value though remains not significant. Thus, in conclusion, there is a more definite trend towards a positive

TABLE 5.7: R&D ANNOUNCEMENTS BY TYPE

SUMMARY OF TWO-DAY [-1, 0] ABNORMAL RETURNS

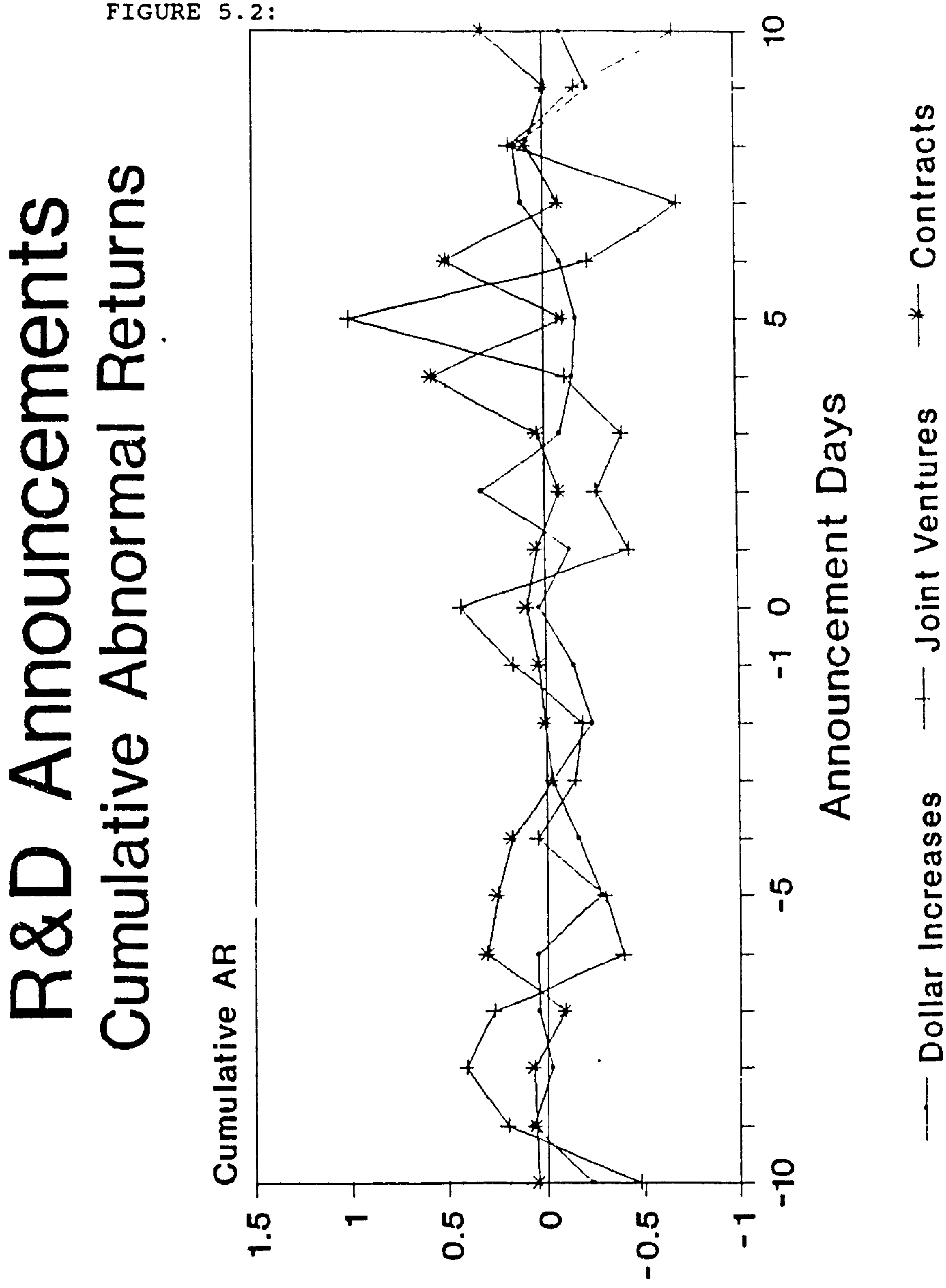
	Dollar Based	Joint Ventures	Contracts
Abnormal Return	-0.093	0.434	-0.295
Z-value	-0.460	1.366	0.545
(p-value)	0.648	(0.1719)	(0.5856)
Standardized Abn Return	-0.090	0.412	0.095
Day 0 Variance AR	1.978	3.446	8.191
Day 1 Variance AR	3.337	4.996	4.437
% negative	61.5	72.7	48.5
Wilcoxon Sign Rank p-value	(0.2346)	(0.2383)	(0.4680)
2-day standard deviation	1.817	3.723	3.861
# Observations	26	11	33

reaction though the reaction remains negative. This positive trend in the 26 announcements is consistent with the results of Chan et. al. Thus while we cannot conclude that the reaction is positive as the existing theory suggests, we can point to this positive trend in the segment of the data set relative to the full sample.

The sample of reactions shows that we have the most narrow sample of abnormal returns to date, with a full 57.6% in the narrow negative bound of -2%<ABN RTN<0%. No returns exceed the 6% upper bound and none exceed the lower bound of -4%. Thus, we do not have to concern ourselves with strong reactions biasing the sample. 84.6% of all returns are concentrated within the region of -2% to 2%. Thus the 15 negative announcements are creating the negative reaction.

The Wilcoxon sign rank value of 61.5% is only slightly below the value of 62% found in the previous sample. The p-value of the sign rank test is 0.2346. The lack of significance though maybe attributable to the small sample size. From a visual analysis of CAR in Figure 5.2, we can see a definite downward bias. The explanation for the large number of negative observations maybe explained by a review of the Chan[1991] article. The reviewer pointed out that the research in the area of R&D expenditures has not conclusively shown one area of negative announcements. According to the reviewer "the possibility that the market responds negatively to R&D investments that occur in the face of decreased short-term earnings is yet to be addressed." [Chan 1991]. The question remains whether there are factors that systematically explain why the stock price response is positive in some cases, but negative in others. The joint venture data set showed the first positive return of the sample. This represents a unique reaction by the market. The reaction is not significant, though the sample is extremely small. The capital market seems to be anticipating a spillover or synergy effect between firms while simultaneously bringing in economies of scale into the R&D process. Thus on the exterior, there seems to be a certification to be gained by combining research talents. The downside is that the joint venture maybe due to the lack of internal innovative prowess.

FIGURE 5.2:



R&D Announcements
Cumulative Abnormal Returns
Cumulative AR
1.5
1
0.5
0
-0.5
-1
-10
-5
-1 0
5
10
Announcement Days
Dollar Increases
Joint Ventures
Contracts

The ambiguity of the result is confirmed by the frequency table wherein one strong positive return is resulting in a positive reaction overall. The stock markets in general do not perceive the joint venture announcement as a significant corporate achievement. This approach to R&D seems to be discounted less favourably than independent research. Perhaps the fear is that the firm will not reap the full benefits of its research or that its internal R&D departments are somehow lacking.

The difficulty in stating that this positive reaction is an important finding stems from the distribution of the sign ranks in the frequency table below. If we examine the Wilcoxon value above, it has a negative value of 72.7%.

Frequency analysis showed that the one extremely positive reaction (greater than 8%) of 10.877 by Eastman Kodak is causing the positive reaction. The Wilcoxon is very negative though it is based on only 11 observations. Thus the basis for joint ventures according to capital markets seems to be relatively weak.

In Figure 5.2 we have a depiction of the CAR values for joint ventures. In this case, there is an up and down pattern found in the announcements of dollar value increases in R&D. The joint ventures seems to be exhibiting an upward spike in the critical [-1,0] interval (reason behind this has been discussed). In addition, ex poste the announcement date there is a large drop in the stock price resulting a devaluation of the market value of the firm.

The ability of a firm to obtain research and development contracts represents a recognition of a successful R&D program. This ability suggests that the firm has superior capabilities vis a vis its competitors.

The expectation is that the market will react most favourably to this type of announcement since it represents a purely external funding source with the possibility of a spillover effect. The results can be said to weakly support this notion. The reaction of the market was a prediction error of -0.295 and a standardized value of 0.095. The original value is weighted down by a number of factors including two highly negative announcements. Nonetheless, the positive standardized value represents the highest reaction yet(excluding the joint ventures previously explained) to an R&D announcement. With the increases in R&D posting a standardized abnormal return of 0.066, this represents the strongest result to date. This can only mean that the stock markets feel that there is some significance to be gained from the 'contract' type of R&D announcements. Since the reaction, though, is not significant, we cannot say that the positive abnormal return is a meaningful result.

If we examine the Wilcoxon sign rank value in the previous table, it is observed that the number of negative reactions drops below 50% for the first time. This represents a substantial change from a full sample rank of 62% and 56.7%

for increases only. This drop in negative reactions is also notable since we have a fairly substantial sample size of 33 announcements. In addition, unlike the joint venture sample, the sample is actually weighted down by two extremely negative announcement effects of over -8%. This is counterbalanced by only one highly positive reaction. Thus the potential for bias is not as strong. The distribution can thus be said to be skewed slightly towards a positive reaction effect. This is a logical result of this type of external R&D funding since the company is not committing its internal funds only. This last section offers the strongest support for our third hypothesis to date.

We have thus concluded that the breakdown of the positive research and development announcements. This has resulted in some interesting results. Some of these though, have been hampered by small sample sizes which allow a strong result in either the negative or positive direction to tilt the entire sample.

The only issue to resolve are the announcements that describe decreases in research and development budgets. This set of announcements represents the strongest likelihood of obtaining a negative abnormal return figure.

TABLE 5.8: NEGATIVE R&D ANNOUNCEMENTS

SUMMARY OF TWO-DAY [-1, 0] ABNORMAL RETURNS

Abnormal Return	-1.602
Z-value	-1.204
(p-value)	(0.2286)
Standardized Abn Return	-0.538
Day 0 Variance AR	0.526
Day 1 Variance AR	2.052
% negative	100
Wilcoxon Sign Rank p-value	(0.0216)
2-day standard deviation	0.830
# Observations	5

As anticipated, the market is perceiving this reaction negatively. The abnormal return of -1.602 is the strongest of any of the segments. The small sample of 5 events results in low Z value. This might be the cause of an insignificant p value. The standardized reaction is -0.538, about one-third the overall reaction. Thus this result confirms the hypothesis that negative research and development reactions are negatively perceived by the market.

Thus, this result at least leads credence to the view that capital markets are not myopic. The investors recognize R&D as a component for the long-term viability of the firm. Therefore, they are selling their shares in the company upon hearing a negative announcement. The Wilcoxon sign rank value bears this out. The value is 100% negative reactions. This represents the first significant Wilcoxon value we have obtained. In this case we have 5 negative reactions listed above. They represent 2 in the 0%>AR>-2% range and the 3 in the -2%>AR >-4% range.

Thus, in conclusion, it seems that R&D announcements are producing a mixed set of results. This suggests that there are underlying variables that must be mitigating the abnormal return analysis. In essence, capital markets are not rewarding research and development expenditures. The following section on new product announcements will prove that capital markets are rewarding the successful output of R&D programs.

CHAPTER 6: NEW PRODUCT ANNOUNCEMENTS

New Products and Innovation:

While the previous chapter examined R&D announcements, this chapter considers new product announcements which can be viewed as the successful output of R&D programs. In our descriptive analysis of the empirical relationship between R&D and patents, we argued that it was highly possible for structural lags to exist, as the output from research and development investment was probably realized over future years. As a result, the relationship between R&D announcements, market perceptions of established R&D programs, and firm value, may not necessarily be contemporaneous. An alternative is to look at new product announcements, which represent the successful output of an internal decision the firm has taken to develop products in a particular area. Thus by evaluating the market's response to new product announcements, we are testing whether capital markets favourably perceive the output of research programs.

Data Collection and Analysis:

The sample was taken from the Dow Jones News Wire and the Dialog Database Services. The sample was from 1979 through until 1988. The announcements were based on searches that were conducted in the Dow Jones Wall Street Journal file. Some examples of the data set are provided. Using the search term 'introduces':

"Centronics Data introduces New Desk-top Graphics Printer"
Date: 12/02/82 Dow Jones WSJ
"Coca-Cola introduces Cherry C ke"
Date: 20/02/85 Dialog WSJ
"Warner's Atari introduces Top of the Line Home Computer"
Date: 13/12/82 Dow Jones WSJ
"AT&T unit introduces PBX product line"
Date: 18/01/83 Dow Jones WSJ

Using the search term 'unveils':
"Eastman Kodak unveils Printing Products Line"
Date: 12/09/83 Dow Jones WSJ
"Cray Research unveiled what it called the world's fastest supercomputer"
Date: 04/06/85 Dialog WSJ
"IBM is seen unveiling its personal computer to counter makers for low-priced clones"
Date: 29/08/86 Dialog WSJ

The data set was allotted a dummy variable code to segregate the announcements on the basis of their potential importance to the firm. The dummy coding separated the data set into three groups which were tested independently. The sample also included announcements that described the introduction of a product into a new market.

The following table describes the distribution of announcements by year. In this 119 firm sample, it may be apparent that the sample has a low concentration of announcements in its first two years. The lowest percent announcements are in 1979. Perhaps representing a pre-recession year as well as a period of high interest rates, companies were less inclined to bring out new products.

The big jump in computer products, particularly in the personal computer market may have created the large boost in announcements in the early mid-1980s. Another factor may have been the fact that companies held back new products during the recession of 1980-82 in order to benefit from an upswing in the economy. This would thus afford better revenues and profit margins. This is perhaps best signified by the bellwether year of 1983 where there were 81 new product announcements, over one sixth of the overall sample.

The interest rate effect mentioned seems to have an inverse effect on new product announcements. The 1979-82 periods were characterized by high interest rates, as was 1986. The new product numbers decreases. This similar hypothesis was developed by Chaney et. al.[1991] in their analysis of new product announcements. The average T-bill rate in 1979 was 8.87% whereas the average in 1980-84 was 10.92%.

It therefore seems that the expectation of future interest rates seems to be creating a downward bias in new product announcements. This may be due to the cost of capital argument. The weighted average cost of capital(WCCA) is a function of the both the beta of the firm and the risk-free rate for a levered firm. As firms expect interest rates to rise, they will reduce their level of investment. On the demand side, rising interest rates can imply a decline in demand, thereby leading to a reduced revenue stream from the innovative processes that are begun(Chaney et. al. [1991]).
The following tables will describe the financial differences between the new product sample and a matching control sample. The matched sample was created using SIC coding. Each firm in

TABLE 6.1: DISTRIBUTION OF ANNOUNCEMENTS BY INDUSTRY

INDUSTRY(2 DIGIT SIC)	#Products	%Products	#Firms	%Firms
Mining & Construction	2	.3	2	1.6
Food	19	3.6	5	3.9
Textiles	3	.6	1	.8
Lumber & Wood	1	.2	1	.8
Paper Products	4	.8	3	2.3
Printing	7	1.3	5	3.9
Chemical/Pharmaceuticals	31	5.9	15	11.7
Petroleum	2	.4	2	1.6
Rubber/Leather	1	.2	1	.8
Metal/Stone work	22	4.2	6	4.7
Computers	189	35.9	25	19.5
Electric Equipment	66	12.5	14	10.9
Transport	8	1.5	5	3.9
Photo Equipment	85	16.1	7	5.5
Miscellaneous	5	0.9	3	2.3
Communications	20	3.8	5	3.9
Electric & Gas Services	1	.2	1	.8
Durable goods	7	1.3	5	3.9
Retail trade	19	3.6	5	3.9
Securities/real estate	16	3.0	5	3.9
Holding companies	14	2.7	6	4.7
Business services	4	.8	5	3.9
Motion Pictures	1	.2	1	.8

the NP announcement sample was matched using 2 digit SIC codes with a firm of comparative asset value. Thus, an optimal match was with a similar firm in the same industry having the same size. The sample size was reduced due to the fact that some firms were unable to be matched effectively.

The first analysis is once again a breakdown of our sample by firm size. This is an asset frequency table. The table suggests that the sample of firms who make new product announcements are larger in general than the average random sample. Over half the firms have asset values in excess of 1 billion dollars. The mean of 1.9 billion suggests that many firms are in excess of 2 billion dollars.

TABLE 6.2: NEW PRODUCT ANNOUNCEMENTS: ASSET SIZES

ASSET SIZE	FREQUENCY	%	CUM FREQ	%
Asset< 20M*	1	0.8	1	0.8
20M<Asset<50M	3	2.5	4	3.3
50M<Asset<250M	13	10.9	17	14.2
250M<Asset<1000M	31	26.1	38	40.3
Asset>1000M	71	59.7	119	100.0

* Millions of dollars

The following is the event-time study of new product announcements. The full number of 527 observations is evaluated based on a 142 firm sample. The event-time table of abnormal returns suggests that there is a substantial positive announcement effect. These findings are similar to those found by Chaney, Devinney and Winer[1991]. The size of the two-day cumulative abnormal return is 0.549%. This is a highly significant result(p-value 0.0016). In the Chaney et. al. study the (-1, +1) average daily return is 0.25%. When the sample was divided into the years 1979-1984 and 1985-1988 the results remain consistent. Therefore, the difference over a period of relative economic stagnation versus economic recovery does not create differences in the results. This lends credence to two important arguments being put forth.

Firstly, it supports Jensen[1986] in his argument against the myopia of capital markets. The study shows that the market reacts favourably to new products and the potential risks they entail. The financing and marketing costs can be

TABLE 6.3: ANNOUNCEMENTS FOR NEW PRODUCTS	
SUMMARY OF TWO-DAY [-1, 0] ABNORMAL RETURNS	
Abnormal Return	0.549
Z-value	3.162
(p-value)	(0.0016)
Standardized Abn Return	0.130
Day 0 Variance AR	4.421
Day 1 Variance AR	6.432
% positive	55.1
Wilcoxon Sign Rank p-value	(0.0039)
2-day standard deviation	3.395
# Observations	527

extensive for new products. This is accepted favourably by capital markets. Also, the fact that a company is announcing new products suggests that it has an active research and development program. This is proved by the intertemporal financial analysis. Finally, the company has successfully navigated the R&D process to produce a product. This suggests a certain amount of competence. Therefore, the positive excess returns generated by these announcements suggest a favourable response by so called 'short-term' investors.

If we examine the CAR of the full sample, we see that there is a pronounced upward trend beginning 8 days prior to the announcement date. This suggests that the information concerning the impending announcement is starting to lift the stock price. The crest occurs 3 days ex poste the

FIGURE 6.1:

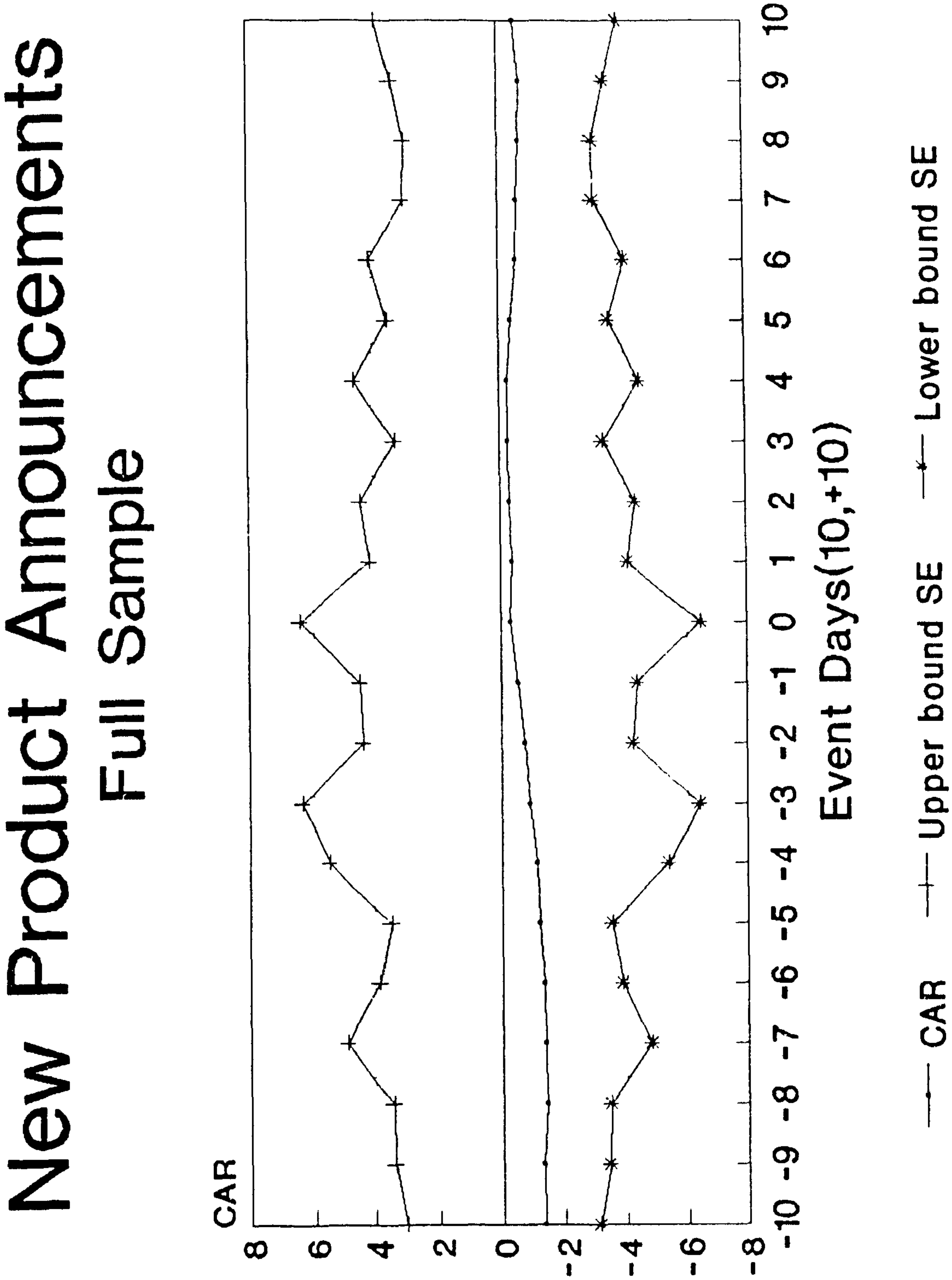

New Product Announcements
Full Sample
CAR
8 6 4 2 0 -2 -4 -6 -8
-10 -9 -8 -7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10
Event Days(10,+10)
CAR
Upper bound SE
Lower bound SE

TABLE 6.4: EXCESS RETURNS BY INDUSTRY FOR DIFFERENT EVENT WINDOWS

Industry(2 Digit SIC)	(-1,0)	(-1,+1)	(-5,+5)
Food[1]	.115	.191	1.568*
	(44.4)	(44.4)	(72.2)*
Textiles	-.227	-1.155	2.229
	(66.7)	(66.7)	(66.7)
Lumber Products	-1.832	-1.654	-3.246
	(25.0)**	(25.0)	(50.0)
Printing	-.435	-.804	-1.836
	(42.9)	(42.9)	(42.9)
Chemical/Pharmaceuticals	.266	.666	.926
	(57.6)	(54.5)	(66.7)
Petroleum	.208	.5[illegible]	.723
	(55.9)	(52.9)	(64.7)
Rubber/Leather	.953**	1.410*	1.367
	(72.7)*	(72.7)	(68.2)
Computers	.143	.170	.194
	(47.9)	(48.9)	(52.1)
Electric Equipment	.647*	.395	.600
	(54.5)**	(47.0)	(56.1)**
Transport	-.584	-.662**	2.173
	(50.0)	(62.5)	(50.0)
Photo Equipment	.690*	.378	2.002*
	(64.1)*	(58.7)	(65.2)
Miscellaneous	4.047*	6.228*	5.747
	(80.0)	(60.0)	(60.0)
Communications	-.563	-.456	-.470
	(40.0)	(45.0)	(55.0)
Durable goods	.622**	2.897	9.025*
	(71.4)**	(57.1)	(57.1)
Retail trade	3.369	4.086*	3.104
	(80.0)	(70.0)	(60.0)
Securities/real estate	.067	-.386	-1.822
	(43.8)	(37.5)	(18.8)
Holding companies	.482	.400	.855
	(57.1)	(57.1)	(64.3)
Business services	-2.094	-2.009	13.669*
	(25.0)*	(25.0)	(75.0)

* at .05 level
** at .10 level
[1] Certain industry results were unavailable due to inadequate sample size.

announcement date. Thus, while the CARs are negative throughout, the upward rise towards and including the announcement day supports the hypothesis that new products are favourably perceived by the market. The breakdown of the overall sample was achieved in order to disseminate new product announcements that are truly exceptional from those that are repetitious. Certain computer companies for example IBM, are constantly introducing a range of new computers. Whether each of these announcements is truly important is suspect. At the same time the introduction of the PC 80286 and PC 80386 computers were significant products. They had the potential to have a significant impact on the operating performance of the company and were pioneer products in the industry. They were creating a new market for personal computers. In addition, some new product announcements describe multiple product releases and are thus more significant.

Thus a coding scheme was developed that defined a new product as 'new', 'new extension' or 'extension'. These were in rank order of importance. The 'new' was the highest order announcement and the 'extension' was the lowest order.

'new' = Dummy code '1'
'new extension' = Dummy code '2'
'extension' = Dummy code '3'

This created three data sets. Examples of this coding can be observed in the following announcements.

'New' : "IBM introduced computer software programs that can link together their personal System/36 and mainframe computers into networks; analysts see this as challenge to Wang because IBM now also has software that runs on different computer models; also, IBM introduced three computers; new AT

personal computer, PC AT/370, new 4381 family intermediate-scale computer and new 308X family mainframe."
Date: Oct 26, 1984 WSJ

'New Extension' : "IBM introduced a new generation of computerized typewriters to succeed its 23 year old Selectric line and increase competition in the booming market for electronic machines."
Date Oct 17, 1984 WSJ

'Extension' : "IBM introduced enhancements for its PC Convertible in an attempt to solve problems that have stalled its sales, changes give computer a better screen, more memory and a modem that is easier to use, but some analysts say enhancements may be too little, too late.
Date: Jan 28, 1987 WSJ

Thus, the first announcement described a new software initiative that had significant network implications. This suggested a new direction for the company which might allow a new market to exploited. In addition, the multiple products announced suggested that this was a highly significant development. The 'new extension' was a new generation of an existing product line. This maybe simply an upgrade from the existing line. Nonetheless, it had sufficient market potential to be given the second order classification. The final announcement was an extension of an existing product. In this case, the company was introducing enhancements to a computer that added up to some moderately improved features. As one article stated, it was probably "too little, too late." Since these product enhancements are unlikely to be significant, they were given the third order rank and placed at the bottom of the scale. Thus, the anticipation was that

TABLE 6.5: ANNOUNCEMENTS FOR NEW PRODUCTS: FIRST ORDER

	SUMMARY OF TWO-DAY [-1, 0] ABNORMAL RETURNS		
	1st Order	2nd Order	3rd Order
Abnormal Return	0.694	0.422	0.140
Z-value (p-value)	3.204 (0.0014)	1.167 (0.2432)	0.37 (0.697)
Standardized Abn Return	0.242	0.098	0.031
Day 0 Variance AR	2.954	4.431	6.136
Day 1 Variance AR	6.556	5.810	6.734
% positive	56.6	53.9	54.2
Wilcoxon Sign Rank p-value	(0.0119)	(0.1125)	(0.1577)
2-day standard deviation	3.298	3.401	3.506
# Observations	192	159	176

these would not have a substantial payoff. The first order announcements exhibits a substantial increase in the abnormal return when compared with the overall sample. The 0.694 return is 50% greater than the 0.431 in the full sample event analysis. The significance of the Z value at 3.204 substantiates this claim. This exceeds the Z statistic of 2.828 in the full sample. In addition, it seems that the coding scheme has effectively segmented the important announcements from those that are less important. These are therefore the 'star' announcements. These are the ones that the corporations and the market recognize as having a significant effect on the profit margin of the firm. The 56.6%

positive reaction announcements is higher than the 55.1% figure from the full sample. Both values are highly significant using the nonparametric Wilcoxon sign rank test. In addition, the effect of one large 20.914% increase by the one observation has a greater impact on a small sample. This value may explain a portion of the increase in the abnormal return statistic. Nonetheless, the Wilcoxon value shows that there were more percentage positive announcements than before. This important statistic confirms the relevance of this high order coding of announcements. For a review of the CAR see Figure 6.2 displayed later on.

The next set of announcements correspond to the second order ranking of the observations. These were defined as the 'new extension' announcements. It is important to note that it was substantially more difficult to separate 'new extension' announcements from simply 'extension' announcements. This may be related to a number of factors.

The first being that the abstract or article may not readily define the importance of the product. This may require an arbitrary decision. In addition, the line between 'new extension' and 'extension' can be subject to some industry specific knowledge. This would require evaluation of the product announcement by an 'expert' which is not feasible for the purposes of this thesis. Lastly, companies may seek to enhance the products they are unveiling or introducing. This may provide the incentive to enhance the prestige or stature of the product to the press in order to increase their share value. Thus with these potential biases in mind, the second order announcement returns can be observed in the following table:

This data set shows a fairly large abnormal return figure of 0.422. This is larger than the third order announcements though it is not significant. This represents a major shift from the highly significant full sample and first order sample. The key factor in this data set is the higher AR value respective to the third order coding.

In the sample, a small number of positive outlier results are dominating the sample of firms. This may explain the high abnormal return figures but the lack of significance of the z-statistic. If we examine the frequency table below, there are 4 observations over the 8% abnormal return figure. In the third order section, this figure was 1.

Therefore, the second order sample is still generating a positive reaction but it does not have the same punch. The numbers are substantially diluted. For information concerning the cumulative abnormal returns(CAR) see Figure 5.2 later on.

This figure displays a dramatic decrease in the abnormal return figure. The value of the [-1, 0] abnormal return stands at 0.140 value. This is far below the previous value for the first and second order reaction and is not significant with a p-value of 0.69. Thus the third order announcements seem to have lost the significant results of the first two samples. An analysis of the frequency of distributions does offer some consolation.

We can see that once again there is an overall positive trend in terms of the number of positive returns found. An analysis of the Wilcoxon sign rank value stands at 54.2%. This figure is only slightly below the 56.6% of the original sample. This third order value is even higher than the second order value of 53.9%(see frequency table) which suggests that there is an overlap in the second and third samples. Nonetheless, the value represents a 0.3% discrepancy which I do not find overly important. The abnormal return value may not be significant due to outlier reactions that affecting the distribution. In addition, a group of negative abnormal returns samples may be responsible for the bulk of the reduction. A discussion of this will be found after an analysis of the third order announcement effects frequencies.

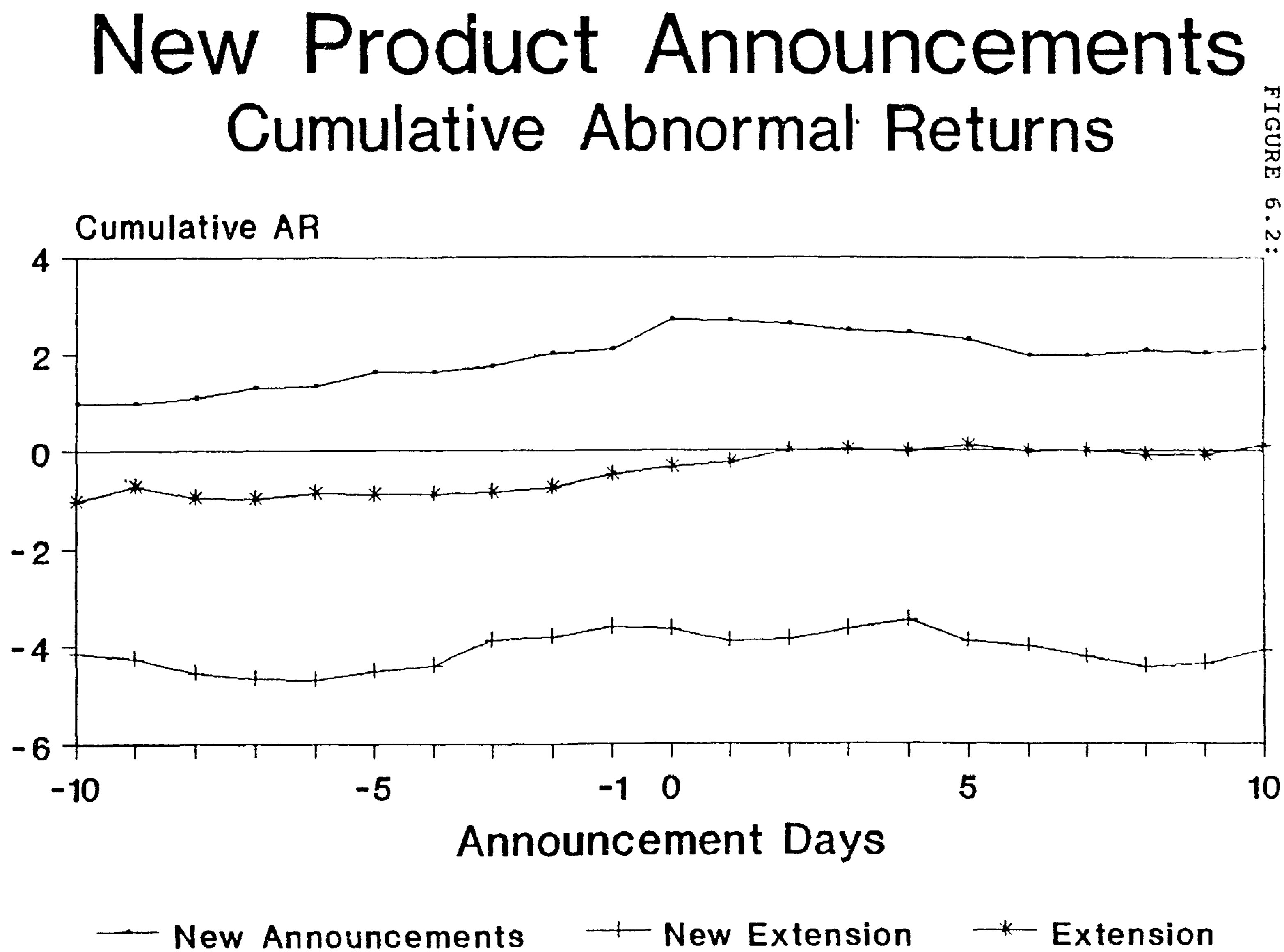
In this case we have an abnormal return of 0.140. This is not significant but there is a highly significant negative reaction of -21.076%. This reaction was generated by Cray Research in 1982. The reaction was in a relation to a new computer. This along with the other abnormal return of less than -8% may have created the drop in the positive AR value. This factor along with the reduction in the high end over 8% abnormal returns results in the weakest results of all the samples.

Nonetheless, the third order reactions were coded only as 'extensions' of existing products and represented the weakest of all the announcements. They did not, in the view of this researcher represent a significant technological advance. Neither did they have the strength of the first and second order reactions in terms of being more than simply a new version of the old product. As the lower results for this order suggest, the reaction is the same as the one of capital markets.

Graphical Analysis and Summary:

The graph in Figure 5.2 shows the cumulative abnormal returns based on the different levels of new product announcements. What is interesting to note is the different levels at which the CARs are moving. Firms announcing 'new' products are maintaining a substantial positive CAR throughout the event period. The market therefore seems to be positively evaluating the firm over an extended period of time. The reverse is happening with the third order announcements which are in the negative range. Thus capital markets are making a marked distinction between the companies. The significance of our overall sample suggests that the market is respecting the new product introductions. The interpretation maybe from the higher expected cash flows that the market expects to generate. Since our intertemporal analysis suggests that significant cash flows result mainly in the second year after the announcement date, this suggests that the market is

FIGURE 6.2:



Segmented Samples

taking a long-term view of the situation rather than the short-term myopic viewpoint often found. Another factor that comes into play is the basis that the market is also acknowledging the company's successful research and development programs. The new product represents a certification of management's innovation and is therefore attempting to re-evaluate the company from that perspective.

CONCLUSION

The analysis of innovative activity in this thesis has resulted in the confirmation of the three hypotheses put forward. From the econometric analysis, a significant relationship was found between corporate R&D and patent counts. The affirmation of this relationship proves that investments in innovation will produce tangible results.

The subsequent analysis of the market's perception of innovative activity was the next step in the analysis. Challenging the concept of market myopia, and without having to specify the functional form of the relationship, new product announcements and R&D announcements were examined. The new products generated a positive and significant reaction. The products represent the end of the innovative cycle of the firm. Their announcement signals successful innovation and the possibility of higher future cash flows. It also represents some indication that capital markets are not myopic in nature and recognize inventive output. The R&D announcements produced positive abnormal returns in the area of joint R&D ventures and external contracts. In addition, their were pronounced negative returns for most of the other types research and development expenditures. The negative signal suggests that the market is not rewarding investments in innovative activity, only its end product.

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