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SCIENCE, TECHNOLOGY AND INNOVATION INDICATORS -A GUIDE FOR POLICY-MAKERS

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TABLE OF CONTENTS

I. SCIENCE, TECHNOLOGY AND INNOVATION INDICATORS - AN OVERVIEW OF THE ISSUES

Keith Smith

Introduction

This report is a guide to the use of data, statistics and indicators for policy-makers working in the fields of science, technology and innovation (hereafter STI). It aims to provide an overview of how the principal quantitative indicators in these fields are constructed, and what they can and cannot tell us about the main questions and dilemmas faced by policy-makers. What kinds of information are STI indicators really providing? How can they be used to analyse problems? To what extent can we make inter-country comparisons with them? These are the types of issues which will be covered in this book.

Terminology

What do we mean by data, statistics and indicators? In this guide we use the following basic terminology to distinguish between these categories. By data, we mean units of quantitative information concerning some process, so that the extent or distribution of the process can be measured - for example, counts of numbers of patents, and their distribution across technical fields, or by country. By statistics, we mean quantitative information collected according to well-defined definitions and sampling or census procedures which enable a description of activity in an entire population - an example would be economic statistics on output, or on the performance of R&D among the firms of a region or country. By indicators, we mean the combination of statistics or data in ways which are essentially analytical - for example, the idea of “R&D intensity”, which is the ratio of R&D expenditure to output for an industry or country, and which suggests the extent to which an industry or a country commits itself to investment in R&D.

Why are indicators a policy issue?

The quality and use of indicators of science, technology and innovation have become an increasingly urgent problem. The basic reason, of course, is that STI policies have been undergoing more or less radical change in concepts, methods and instruments, as policy-

makers seek to use STI policy to achieve new and wider goals related to growth, employment and international competitiveness. Both in the EU and the G7 more generally we have seen long-run declines in the growth rates of output and productivity, persistent high levels of unemployment, and increasing income dispersion (accompanied in some countries by marginalisation of significant sections of the populations). At the same time, we are clearly living through major technological revolutions in such fields as IT, biotechnology and materials, which involve complex interactions between government, industry and the science system. More generally, production processes across industries are being changed - often dramatically - by innovation and the impact of new generic technologies, and we are seeing persistent change in company and industry-level organizational structures. The latter are having major impacts on employment patterns and income dispersion, and have serious implications for employment and training policies. A key question, of course, concerns the intersection between these processes: what are the links between the dramatic economic and technological changes of the past two decades, and what are the implications for policy?

Regardless of what the causal interactions might be in detail, policy-makers have seen a strong connection between growth/employment issues and technological change. In 1980, the OECD published an influential analysis of the 'stagflation' crisis of the 1970s. *Technical Change and Economic Policy* shifted policy analysis away from the field of short-run macroeconomic fluctuations, where developments had been debated in terms of Keynesian versus free-market macroeconomic policies. It argued that the crisis had a structural character, with the slowdown in productivity growth having its roots in the rate and direction of technological innovation. Since innovation is powerfully influenced by policy decisions, it concluded that "technological innovation, far from being peripheral, is central to the solution of these problems ... research and innovation policies must be better integrated with other aspects of government policy, particularly with economic and social ones."[1] The report pointed to continuing problems in the availability of suitable economic indicators for mapping and analysing the changes which were underway.

Such ideas have had a powerful impact on the evolution of policy thinking at national and transnational level since the early 1980s. Firstly, there have been changes in the explicit

[1] OECD, Technical Change and Economic Policy. Science and Technology in the New Economic Context (OECD:Paris), 1980, p.15

objectives of policy actions: during the 1980s, STI policies became - in most countries - explicitly oriented towards enhancing competitiveness. This extended into European-level initiatives, with the emergence of the FRAMEWORK programmes, whose primary objective is "to increase the competitiveness of European industry". Secondly, policy-makers have come to see STI policy in a more ambitious way: as a key tool for the achievement of very wide policy objectives. Within the G7, for example, the deep concern with unemployment has led to an increasing volume of policy analysis, but this analysis has focused overwhelmingly on STI issues: the recent report from OECD to the G7, *Technology, Productivity and Job Creation* is an example of this.[2] Within the EU, both the Maastricht Treaty, and the White Paper on unemployment, see STI policy as having a crucial role in European competitiveness and social cohesion. [3] This concern has been reflected in action. Policy actions in this field take a variety of forms, but if for example we confine ourselves to research and development expenditure, then the 50 largest R&D-performing economies are each spending between 1.5 and 2.5 percent of Gross Domestic Product on R&D, which came to a total of just over 350 billion ECU in 1996.[4] About half of this was government-funded. This is, in itself, a substantial commitment of resources. In the EU, the budget of FRAMEWORK, the overall R&D programme budget, is one of the growing areas, and its future conceptual underpinnings and scope are a major policy issue. But the policy objectives are also far-reaching: science and technology policy is largely based on the recognition by governments that innovation and technological change are the fundamental driving forces in the growth of output, productivity and hence of real per capita incomes. Since such growth has been the most important factor shaping the extraordinary welfare improvements achieved by the advanced economies over the past two hundred years, the returns to any activity which promotes technological advance are potentially very large indeed. From this follows the importance of public policy as an activity promoting such advance.

This expansion of the ambition of policy has however raised quite fundamental issues about our conceptual and empirical knowledge of processes of knowledge creation and their links

[2] OECD , Technology, Productivity and Job Creation (OECD:Paris) 1996.

[3] For a discussion of the RTD implications of the Maastricht treaty, see Research After Maastricht: an assessment, a strategy, Bulletin of the European Communities, Supplement 2/92; for links between RTD and wider economic objectives see Commission of the European Communities, Growth, Competitiveness, Employment. The Challenges and Ways Forward into the 21t Century (White Paper), Bulletin of the European Communities, Supplement 6/93.

[4] Second European Report on Science and Technology Indicators 1997, *Appendix,* Table A.2.1, p.S-8.

with economic and social outcomes. We have a growing body of research which has changed our understanding of the characteristics and economic results of innovation, and much of this research provides theoretical and empirical support to the links between innovation-oriented policies and broader economic policy. For example recent years have seen a resurgence in theorising about economic growth, both from evolutionary standpoints and in the so-called 'new neo-classical growth theory'. In many of these models, the basic process used to explain economic growth is the phenomenon of increasing returns to scale, following from the externality aspects of R&D and technological change.[5] Several of the most important approaches within this field involve modelling a specific 'research sector' of the economy, which produces both specific new inputs, plus general scientific and technical knowledge. In these models, growth results partly from increases in the productivity of tools and equipment (intermediate inputs) resulting from technological change, and partly from 'spillovers' of knowledge from one area to another.

The study of economic growth is rapidly changing, and there remains no overall theoretical consensus. But it is very important to note that for the first time we now have a significant body of economic theory which explicitly relates the R&D system (however abstractly it is modelled) to the economic growth process. But we also have long-standing results from applied economic research on these issues. Four empirical results are widely accepted, namely that:[6]

- technical change is the most important explanatory factor in economic growth,
- innovation performance (as measured by science and technology variables) underlies export performance and shares of world trade,
- R&D is closely linked to the explanation of firm-level productivity growth,
- rates of return to investment in R&D - even basic R&D in the university system - are high. Social returns to R&D are consistently higher than private returns.

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[5] For an excellent survey, see Bart Verspagen, 'Endogenous innovation in neo-classical growth models', Journal of Macroeconomics, Vol 14 No 4, 1992, pp.631-662. More recently, Paul Romer 'The origins of endogenous growth', Journal of Economic Perspectives, Vol 8 No 1, 1994, pp.3-22, and G. Grossman and E. Helpman, 'Endogenous innovation in the theory of growth', Journal of Economic Perspectives , Vol 8 No 1, 1994, pp. 23-44. On policy aspects of new growth models see G.K. Shaw, 'Policy Implications of Endogenous Growth theory', Economic Journal, Vol 102 No 412, 1992, pp.611-622.

[6] See, for example, C. Freeman (ed) Output Measurement in Science and Technology, (Amsterdam: North Holland), 1987; Jan Fagerberg, 'International Competitiveness', Economic Journal, Vol 98 No 391, 1988; Z. Griliches, R&D, Patents and Productivity (Chicago, 1986); G. Dosi, K. Pavitt and L. Soete, The Economics of Technical Change and International Trade, 1990.

Indicator challenges

There remain serious problems concerning our ability to draw on the results of this research in policy formation and implementation. In few areas are the limitations of available data more severe than in innovation and technological change. At the same time there has been a rapidly increasing demand for quantitative information: for the collection and presentation of relevant data, often with international comparisons. So all EU Member States, and most OECD member governments, prepare data and report on R&D expenditures, and on a varying range of other STI indicators. In the US, the National Science Foundation has for some years presented a comprehensive overview of *Science and Engineering Indicators* covering all aspects of R&D and the science and engineering workforce. In Europe, the European Commission is now regularly preparing an extremely ambitious quantitative overview not only of European R&D and innovation activity, but also of major international comparisons.[7]

This work has led to serious questions about the adequacy of existing data and indicators for policy, both in terms of their basic design, and in terms of how they can be interpreted and improved. At the same time we have seen attempts to create new and better-designed indicators: for example, the European Commission has supported large-scale efforts to overcome the absence of direct data on industrial innovation – and there have been important other attempts to improve our knowledge of outputs, sources, instruments and methods of innovation.[8]

The generally available data for innovation and technology analysis is essentially of four types. Firstly, there is data on R&D inputs, collected in the OECD economies according to the procedures and categories described in the "Frascati Manual".[9] Secondly, there is patent data, the most important body of which consists of the records of the US Patent Office and the European Patent Office. Thirdly, there is bibliometric data on patterns of scientific publication and citation. Finally, there are various new types of data seeking to directly

[7] European Commission, The European Report on Science and Technology Indicators 1994 (EUR 15897), 1994; and Second European Report on Science and Technology Indicators 1994 (EUR 17639), 1997.

[8] See European Commission, The Community Innovation Survey - Status and Perspectives (Luxembourg 1994); Arundel A., van de Paal G., Soete L. Innovation Strategies of Europe's Largest Industrial Firms: Results of the PACE Survey of Information Sources, Public Research, Protection of Innovations, and Government Programmes. MERIT, March 1995.

measure or indicate innovation processes across sectors: their inputs, outputs, objectives and so on. In addition to these major sources, there exists a wide range of what we might call 'ad hoc' data sources, constructed usually by researchers to explore specific research issues.

The fact that these data sources have limitations is well known. R&D numbers measure only an input, which has no necessary relation to innovation outcomes. There are many examples of successful innovating companies which perform relatively little R&D. Patent data is limited by variations in firms' and industries' propensity to patent; moreover it tells us only about the invention phase of the innovation process, and little about commercialisation and hence the economic value or economic impact of an invention. It may also be, as Keith Pavitt has argued, that R&D data underestimates the amount of innovative activity in small firms, while patent data underestimates innovation in large firms.[10] Bibliometric data tells us much about the changing shape of fundamental research, but little about the innovation process. Innovation data faces basic challenges in capturing all aspects of the novelty, learning and change which are involved in innovation.

Interpreting data, statistics and indicators: general background

Nevertheless there is very much that can be done with the data and indicators we have, and with those that are under development. But it is always very important to bear in mind their strengths and limitations, and the sometimes subtle problems involved in interpreting these indicators. The later chapters of this guide provide detailed discussions of these interpretative issues with respect to the main categories of indicators mentioned above.

Behind these interpretative issues are a number of general 'principles' concerning indicators which should be kept in mind. Four such principles, often closely relevant to STI indicators, are as follows:

1. Statistics always have an implicit or explicit conceptual basis.

Statistics are not simply numbers. They always have some kind of conceptual basis, if only because of the fact that they must in some way define the object which is being measured. In

[9] OECD, The Measurement of Scientific and Technical Activities, "Frascati Manual 1980", (OECD: Paris, 1981).

[10] Keith Pavitt, "R&D, patenting and innovative activities. A statistical exploration", Research Policy, Vol 11 No 1, 1982, pp.33-51.

some case the conceptual basis can be explicitly theoretical. For example the System of National Accounts, which measures national income in all EU Member States and most other countries is closely related to the macroeconomic theory developed by Keynes; the system began as an attempt to classify and measure the main categories of aggregate demand, the changes in which underlay short-run fluctuations in economic activity. In other cases, definitions may have no explicit theoretical basis, but rather have an implicit conceptual underpinning to do with the "accepted wisdom" of practitioners or experts in a field. In such cases, definitions tend to be marked by the historical context, and it can be important to bear this in mind. An important example here are the definitions of Research and Development used in most OECD countries; they were drawn up in ways which reflected views at the time concerning the nature and role of R&D, and - as we shall show in a later chapter - this can give rise to difficulties both in interpretation and in modifying the definitions of R&D to take account of more recent concerns.

2. Some key sources of data are produced as a by-product of non-statistical processes

There are some important data sources in the STI field which are essentially derivative from some other process, and which do not have any explicitly statistical basis at all. For example, patent data is the outcome of a legal process through which property rights in knowledge are created, and the validity of a patent depends for example on legal definitions concerning what is new in the "state of the art" in some field. There are legal constraints on what can be patented, and often complex conflict over the patentability of some invention - genetically engineered organisms are an example of this at the present time. Bibliometric data - that is data on fundamental scientific article publications in certain types of journals - reflects not a legal process but rather a cultural one: conventions within academic life concerning the role of scientific publishing in establishing priority in discovery, and conventions concerning how and when a researcher cites the work of others in his or her work. These background legal and conventional frameworks have important implications for what the data can actually tell us, as we shall see in a later chapter.

3. Statistics often have implicit social foundations

The legal and cultural processes referred to above can extend into a wider social shaping of statistics, especially through definitions which reflect changing social concerns about some phenomenon. An example here might be poverty indicators and conceptions of poverty, which in some case are defined in rather absolute terms - as access to certain minimum quantities of nutrition, medical care and so on. But poverty can also be defined in relative terms, and so

within advanced economies in particular it is widely accepted that some people with levels of consumption which are quite high in historical or comparative terms can nevertheless be poor.

4. Statistics are often marked by the policy context

It obvious to everyone that statistics and indicators often have political significance - political debate often takes the form of arguments over income growth, inflation rates, tax burden and so on. But it would be naive not to recognise that political concerns can also affect statistical definitions and the indicators derived from them. A major example of this, in some EU Member States, is the unemployment rate. As noted above, persistent unemployment is one of the major policy problems of our time. One response, by some governments, has been to revise the technical definitions of who is unemployed; and it is not unheard of for a government to claim an outstanding performance on unemployment on the basis of essentially statistical changes. While this kind of redefinition is not a serious problem in the field of STI statistics, it would probably be wrong to think that increasing government attention to indicators in this field has no effects at all.

Coverage of this 'Guide'

This Guide covers four main areas of STI indicators Chapter One looks at direct indicators of innovation inputs and outputs, with a close look at the largest new indicator source, the *Community Innovation Survey*. Chapter Two looks at research and Development (R&D) data, focusing closely on the problems which are involved in using such data to make international comparisons of R&D effort. Chapter Three looks at patenting, looking at both historical and contemporary uses of patent data, and emphasing the many uses to which this data can be put, and the need to understand the different contexts in which patent data is generated. Chapter Four discusses bibliometric data, again showing the wide range of potential insights which can be gained, but emphasing the need for a close understanding of how the data is produced. Chapter Five examines three important research databases, and their potential uses: these are the Science Policy Research Unit's 'Large firms' database, the MERIT database on strategic alliances and co-operative agreements, and finally recent OECD-sponsored databases on technological collaboration and networking among firms.

II. INNOVATION INDICATORS

Keith Smith

1. INTRODUCTION

Is it important to build direct indicators of innovation? To what extent can we measure inputs and outputs of the innovation process within firms? This chapter discusses recent attempts to measure innovation, looking at the ways innovation measurement has been tackled, at the underlying conceptual issues, and at some of the main results and at remaining challenges.

There have been major efforts in the field of innovation indicator development over the past decade, efforts driven both by policy concerns and by theorists and analysts. From the policy side there has been an increasing understanding and awareness of the economic importance of innovation, and a tighter linkage between innovation policy and wider policy objectives. From the theoretical or analytical side, the study of the characteristics and impacts of innovation began to accelerate nearly thirty years ago and has now become a major research area for economic analysis and general social theory. These combined impulses have led researchers and institutions to seek to develop better quantitative indicators for the economy as a whole. However this goal grew substantially in importance in the early 1990s as major institutions such as the OECD and the European Commission began the process of defining innovation indicators, and coordinating their implementation across countries. These initiatives led, for example, to the OECD's *Oslo Manual*, first published in 1992 and revised in 1997, which attempted to provide theoretical and methodological foundations and guidelines for new innovation indicators, and to the C*ommunity Innovation Survey*, funded by the European Commission via Eurostat, and implemented in 1992-93, and again 1997-98. The latter exercise has involved data collection from a very substantial number of firms: more than 40,000 in the first round, and probably around 80,000 in the second round.

The policy need for new innovation indicators is based on a recognition of the vital role of innovation in modem economies. This has sharply increased the importance of R&D and innovation policy. Both are no longer seen as separate and somewhat peripheral areas within the overall policy agenda. Instead, innovation policy is now viewed as an essential instrument for achieving important social and economic goals, because of the central role of innovation in

economic growth, competitiveness and trade. Virtually all of the work by the OECD on unemployment in the last couple of years has focused on the importance of innovation and new technology to improving the employment picture1 and innovation is also central to the European Commission's *White Paper on Employment and Competitiveness in Europe.*[1] The policy focus on innovation is clearly seen in the Maastricht Treaty, which contains a section on R&D policy within the context of the wider objectives of the EU, and this theme is continued in the *Action Plan on Innovation* that was recently published by DG XIII. More significantly still, the *Fifth Framework Programme* clearly links research and innovation policy to wider policy objectives for the European society and economy.

Once we start looking at policy questions, however, we immediately run into a situation in which the diagnosis of the causes of problems and the recommended solutions are sometimes based on very sparse evidence. For example, it is sometimes argued that labour mobility – especially of researchers - is excessively low in Europe; but we don't have any general statistics to properly evaluate this. Similarly, from time to time it is suggested that innovation performance in Europe is less satisfactory than in the United States or Japan. Once again, we really do not have comparable data to determine where this diagnosis is really true: for example, is it true that in general European innovation performance is relatively weak, or is this something which is true only of certain sectors or certain countries, or is it simply not true at all? Often, policy conclusions in Europe have been derived from case studies or partial statistics, because the type of empirical data that is needed to fully evaluate these issues has simply been missing.

[1] See *Technology, Productivity and Job Creation*, OECD, Paris, 1996.

2. WHY ARE MEASUREMENT ISSUES IMPORTANT IN INNOVATION STUDIES?

Why is it important to have a statistical approach to innovation at all, rather than using case studies or other partial approaches (which incidentally have the merit of being cheap to perform compared to statistical work)? The basic reason is that many theories about innovation or about its effects, for example theories of economic growth, really concern propositions about systems or populations. This means that the testing of these propositions should not be based on the generalisation of a few examples, such as those drawn from case studies. There is an enormous amount of extremely valuable case studies that have enriched our understanding of innovation, but these studies simply do not cover all relevant sectors or technologies; on the contrary, many of the innovation case studies of the past twenty years are focused on a relatively small group of R&D-intensive sectors of the economy. The result is that many innovation theories, particularly when extended to dynamics and growth theory, have only a tenuous link with economy-wide evidence. Since we are interested in the characteristics, structure, and dynamics of populations and natural systems as a whole, we need data that reflects the entirety of a population of firms.

We do, of course, already have some general indicators, particularly in the form of R&D statistics and patent data. But as we noted in the introduction, they all have serious empirical limitations: in general, they allow to look only at one piece of the innovation picture. The limitations to existing empirical data provide good reasons for developing new indicators that can more fully encompass innovation processes.

3. THE CONCEPTUAL BACKGROUND: MEASUREMENT ISSUES

It must be said at the outset that there are very fundamental problems in seeking to measure innovation at all, both in terms of inputs to innovation, and in terms of outputs of the innovation process. It can be strongly argued that in certain respects innovation is incompatible with measurement *tout court*. Measurement is a process of counting or comparison in which we seek to compare entities in terms of some common characteristics, such as weight, dimensions, and so on. In other words, measurement requires an *a priori* dimensional similarity between objects; that is, there is some dimension along which they are meaningfully share attributes. People can be tall or short, fat or thin, but they share relatively simple attributes of size which make various types of measurement possible. Measurement

implies commensurability: that there is at least some level on which entities are qualitatively similar, so that comparisons can then be made in quantitative terms.

However innovation is, by definition, novelty. It is the creation of something qualitatively new, and this leads immediately to problems in measuring and comparing. Innovation is not about extending pre-existing dimensions, but rather changing or replacing technical attributes. In some cases this may mean changing product characteristics, or combinations of characteristics, which may certainly be intrinsically measurable in some way - the lift/drag aspects of an aircraft wing, for example, or the speed/carrying-capacity combination of an entire aircraft. However such technical measurement comparisons are only rarely meaningful across products. It is difficult if not impossible to assess by means of technical measurements of attributes to assess, for example, the degree of innovativeness of a product. More generally, innovation involves multi-dimensional novelty in aspects of activity or knowledge organization which are difficult to measure or intrinsically unmeasurable. A related problem - with human beings - might be attempts to measure intelligence rather than height or weight; the multi-faceted characteristics which make up intelligence in people, and which exist in often suprising combinations, do not readily lend themselves to any measurement concept.

This does not mean that measurement approaches cannot be developed, but such measurements usually involve a practice of reduction to some manageable measurement analogue. The question then is, does such a reduction maintain a real link to the process being measured, such that we might be justified in treating the measurement process as in some way representative of the underlying object of interest? In practice, this issue is often somewhat ignored. What, for example, is the conceptual link between IQ tests and the notion of ‘intelligence’ which they are supposedly exploring? If such a link is explicit and itself conceptually clear, then we might be justified in using the results of IQ tests for some purposes. If not, then the attempt at measurement is likely to obscure more than it clarifies.

So some main issues in constructing innovation indicators concern, for example, the meaning of the measurement concept which is used, the scope of measurement exercises, the underlying theory, and the general feasibility of different types of measurement. Problems of commensurability are not necessarily insoluble, but one of the main points to emerge from recent indicator development is that we must be very careful in distinguishing between what can and what cannot be measured in innovation.

Quite apart from the problem of whether novelty can be measured, a fundamental definitional issue is to decide what we actually mean by "new". Does an innovation have to contain a basic new principle that has never been used in the world before, or does it only need to be new to a firm? Does an innovation have to incorporate a radically novel idea, or only an incremental change? In general, the question is; what kind of novelty counts as an innovation? Researchers and statisticians must decide whether they only look at path-breaking innovations that are new to the world, or also at small-scale, localised change: some or all of these new products could incorporate incremental changes or they could have already been introduced onto a market by another firm.

Such underlying conceptual issues are very much present in innovation analysis. Case studies of innovation invariably suggest considerable complexity and diversity of innovation processes across firms and industries. Perhaps the single biggest case study of innovation processes, the Minnesota Innovation Research Project in the US, emphasized that its primary result was ‘a complicated, somewhat unruly set of empirical observations that described the multi-faceted nature of innovations and that are often beyond the explanatory capabilities of existing innovation theories’ (Poole and Van der Ven, 1988: 637). But if there is great variation in innovation processes, in terms of their objectives, organisation, cost, use of research, and so on, then it also means that there is variation in the problems and constraints which firms must overcome in order to undertake successful technological change.

This suggests two basic objectives for any conceptual approach to the measurement of innovation. The first objective is to discriminate between those aspects of the innovation process which can and cannot be measured. The second is to clarify the links between the measurement approach and the underlying process.

4. THEORIES OF INNOVATION

Where do we stand in terms of theoretical ideas which can give us some guide to understanding the innovation process? The basic background for almost all modern work is the work of Joseph Schumpeter, and it seems reasonable to start with his contribution, and the various rejections and developments of it which have shaped recent analysis.

Schumpeter argued that to produce "means to combine materials and forces within our reach", and that economic development entails the discontinuous introduction of "new combinations"; the formation of these new combinations is the innovative process. In his **Theory of Economic Development,** this involves five types of activity:

- Introduction of a new product or a qualitative change in an existing product;
- Process innovation new to an industry (which need not therefore involve new knowledge);
- "The opening of a new market";
- Development of new sources of supply for raw materials or other inputs;
- Changes in industrial organisation.[2]

Thirty years later, in **Capitalism, Socialism and Democracy**, Schumpeter reiterated that these forms of change remained "the fundamental impulse that sets and keeps the capitalist engine in motion" (p.83), although by then he regarded the possibilities of the latter three factors as diminished by developments since the late 19th century. Entrepreneurship is that form of competitive behaviour which seeks such new combinations. In that sense, therefore, it does not refer to human agents: it is a function, a component of economic activity. Thus it may (and often does) involve far-sighted, driven individuals or small mould-breaking enterprises. But it it also a function which large enterprises must fulfil if they are to survive, and it is therefore a permanent component of micro-economic behaviour. The outcome is a process of "industrial mutation" that incessantly revolutionizes the economic structure “from within”, incessantly destroying the old one, incessantly creating the new one. This process of “creative destruction” is the essential fact about capitalism. It is what capitalism consists in and what every capitalist concern has to live in.(CSD p.83) It is important to note here that Schumpeter saw innovation as the introduction of decisively new products, which more or less radically changed the competitive environment:

> ... in capitalist reality as distinguished from its text book picture, it is not (proce) competition which counts but the competition from the new commodity, the new technology, the new source of supply, the new type of organisation ... competition which commands a decisive cost or quality advantage and which strikes not at the margins of the profits and outputs of existing firms but at their foundations and their very lives.

[2] See J.A. Schumpeter, The Theory of Economic Development, p.66.

Within this broad approach to innovation, Schumpeter proposed three basic phases in the innovation process:

- invention, a process of discovery of new technical principles
- innovation, a process of development of an invention into a basically commercial form
- diffusion, or the spread of an innovation into commercial use

In both the or less strict demaracation between these phases, and in the underlying concept of innovation, Schumpeter has had a continuing impact on both theory and measurement concepts. For example, patents, in registering a clear advance in the technical 'state of the art' are clearly an indicator of invention in the Schumpeterian sense. And R&D data, in emphasizing the search for completely new knowledge, reflects the underlying Schumpeterian concept of an innovation as involving a significant break with the past of a technology.

However a significant amount of modern work, and especially the more important parts of it, have in effect consisted of a more or less sustained attack on Schumpeters phase model of innovation. The most important figure here has been Nathan Rosenberg. In a sustained series of papers, Rosenberg has in particular challenged the notion of separability between innovation and diffusion processes, pointing out that most diffusion processes involve long and cumulative programmes of post-commercialisation improvements in technologies, and that innovative success and the diffusion process are often linked with innovative improvements in complementary technologies. However he has also in effect challenged the notion of prior invention as a preliminary phase of innovation. Here his major contribution, with Steven Kline, has been the so-called chain-link model of innovation, which stresses three basic aspects of innovation:

- innovation is not a sequential process but one involving many interactions and feedbacks
- innovation is a process involving multi-faceted inputs
- innovation does not depend on invention processes (in the sense of discovery of new principles), and such processes (involving formal R&D) tend to be undertaken as problem-solving within an ongoing innovation process rather than an initiating factor

The work of Rosenberg alone, and secondly of Rosenberg and Kline has two important implications for indicator development. The first lies in the importance of incremental improvement, in relatively small scale changes in product performance which may – over a long period – have major technological and economic implications. The second implication is

the importance of non-R&D inputs to innovation – the importance of design activities, of engineering developments and experimentation, of training, and so on. It is these ideas which have driven much of recent indicator development.

5. TYPES OF INNOVATION SURVEY AND THEIR HISTORY

Most recent innovation indicator development has been based on surveys. These surveys divide into two basic types: those which focus on *firm-level innovation activity*, asking about general innovation inputs (both R&D and non-R&D) and outputs (usually of product innovations), and those which focus on *significant technological innovations* (usually identified through expert appraisal, or through new product announcements in trade journals or other literature). Sometimes the first of these approaches is called a 'subject' approach, since it focuses on the innovating agent; the latter is referred to as the 'object' approach, since it focuses on the objective output of the innovation process, on the technology itself. The subject approach focuses on the innovator, while the object approach focuses on the innovation. Both approaches can and do incorporate attempts to explore aspects of the innovation process itself: sources of innovative ideas, external inputs, users of innovation, and so on. Both approaches define an innovation in the Schumpeterian sense, as the commercialization of a new product or process; but the object approach tends to focus on significantly new products, while the subject approach includes small-scale, incremental change.

Table 2.1: The nature of innovation surveys

	INNOVATION SURVEYS	
	'Object approach'	***'Subject approach'***
Unit of analysis	Technological innovations	Firms
Origin of the information	Collected for analytical purposes	Collected for analytical and/or policy purposes
Method of collecting information	Collected from different sources such as new product announcements, expert surveys, innovation inventories, bibliometric directories	Collected at the firm level, usually by mail questionnaires
Periodicity	Occasional surveys	Occasional surveys. Now Data collection is becoming periodical via CIS
Coverage	Samples of successful innovations, informs on innovation introduced by both the business and the non-profit sectors	Successful and unsuccessful innovative activities. Innovating and non-innovating firms. Includes manufacturing and service industries
Main criteria of classification	Product. Firm's principal economic activity	Firm's principal economic activity. Main user sector. Firm size.

Source: Archibugi & Pianta (1996) p. 20

6. THE 'OBJECT' APPROACH TO INNOVATION INDICATORS

Perhaps the most important example of the 'object' approach is the SPRU database, developed by the Science Policy Research Unit at the University of Sussex, which collected information on major technical innovations in British industry, covering sources and types of innovation, industry innovation patterns, cross-industry linkages, regional aspects and so on.[3] The SPRU approach used a panel of about 400 technical experts, drawn from a range of institutions, to identify major innovations across all sectors of the economy, from 1945 through to 1983. The database covers a total of about 4,300 innovations. An important related database is the US Small Business Administration database, covering innovations introduced to the market by small firms in the US in one year, 1982. This was constructed through an examination of about one hundred trade, engineering and technology journals.[4] In addition

[3] See J. Townsend, F. Henwood, G. Thomas, K. Pavitt and S. Wyatt, Innovations in Britain Since 1945, SPRU Occasional Paper No 16, 1981. For analyses using the SPRU database, see for example K. Pavitt, "Some characteristics of innovation activities in British industry", Omega, Vol 11, 1983, and M. Robson, J. Townsend and K. Pavitt, "Sectoral patterns of production and use of innovations in the UK: 1945-1983", Research Policy, Vol 17 No 1, 1988, pp.1-15. The most recent sustained analytical work using the SPRU database is Paul Geroski, Market Structure, Corporate performance and Innovative Activity (Clarendon press, Oxford), 1994

[4] A major study has been based upon it: Z. Acs and D. Audretsch, Innovation and Small Firms (Cambridge, Mass., 1990).

there are a range of smaller literature-based surveys which have been undertaken in recent years: the Netherlands, Austria, Ireland and the UK are examples.[5]

This type of approach has a number of strong advantages. Technology-oriented approaches have the merit of focussing on the technology itself, and allow a form of external assessment of the importance of an innovation – the fact that an innovation is recognised by an expert or a trade journal makes the counting of an innovation somewhat independent of personal judgements about what is or is not an innovation. Both expert-based and literature-based approaches can be backward looking, and give an evolutionary perspective on technological development. Most of these approaches illuminate sectoral patterns in technology development

But the approach also has weaknesses. The very fact that innovations must pass a test of significance - that is, must be sufficiently innovative to be publicised in trade journals or the general press - also imparts a sample selection bias to the exercise. In effect what these surveys cover is an important subset of the population of innovations: those which are new to an industry. What gets lost is the population of innovation outputs which are "routine", incremental, part of the normal competitive activity of firms, yet not strikingly new enough to be reported. A final problem is that such technology-oriented surveys do not involve assessments of the economic significance of innovations.

7. RESULTS

One of the most important results of work using the SPRU database was to show the existence of quite different types of innovative activity across different types of industry. In a pioneering paper in the early 1980s, Pavitt distinguished between four basic firm types, which he called ‘science based’, ‘scale intensive’, ‘specialised suppliers’ and ‘supplier dominated’.[6] He showed that these categories of firms were characterised by differences in sources of technology, types of users, means of appropriation, typical firm size and so on. Supplier-dominated firms were characterised by external sources of technology, by a focus on process

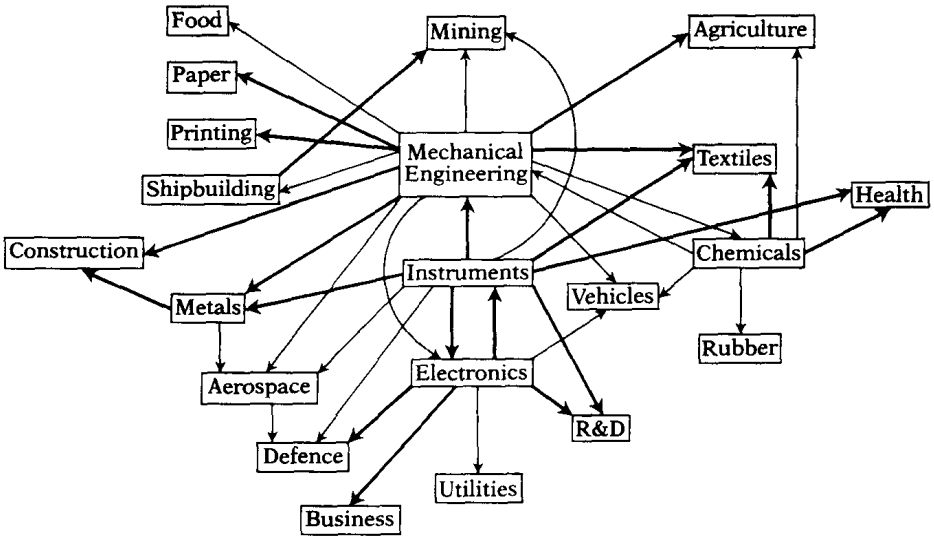
[5] The best overviews are A. Kleinknecht and D. Bain (eds), New Concepts in Innovation Output Measurement (London: Macmillan) 1993, and A. Kleinknecht (ed) Determinants of Innovation. The Message From New Indicators, (London: Macmillan) 1996.

[6] Keith Pavitt, ‘Sectoral patterns of technological change: towards a taxonomy and a theory’, Research Policy, 13 (1984), 343-373.

innovation and by appropriation regimes in which non-technical factors (marketing, trade marks and so on) were central. Science-based firms dpended much more on internal R&D as a competitive factor. Their means of appropriation were patents and know-how, with product design an important part of a a dynamic learning capability. Scale-intensive firms had technological trajectories in the direction of cost-cutting and product design. Finally, specialised suppliers catered to performance-sensitive users, and therefore had technological trajectories heavily focused on product innovation. Operating in machinery and instruments manufacture, they relied on design and on users for sources of technology.

This work was among the first to really demonstrate empirically the importance of technological diversity within the economy, with important implications for the design of R&D policy in circumstances where firms have very different technology creation patterns. Other work with the SPRU database has emphasised the inter-sectoral flow of innovations (using the important data on first users of innovations within the dataset), and gave an early empirical insight into the complexity of what is now called the system of innovation. Geroski (1994, p.19) has summarised these intersectoral flows as shown in Figure 2.1.:

Figure 2.1.The SPRU innovation database:The intersectoral flow of innovations



Source: Geroski (1994)

The key result here is the importance of the three major enginneering sectors (mechanical engineering, instruments and electronic engineering) in terms of the flow of innovations into

other sectors. But it is important to note also the importance of flows within this broad engineering complex.

8.THE SUBJECT APPROACH

It is the much wider subset of innovations which are new for a company, but not otherwise noteworthy, which are included in the second category, namely surveys of companies. Company-level innovation surveys began in the early 1980s, led by individual researchers seeking develop workable measures and datasets; various types of survey were carried out in Germany, Italy, France, and Scandinavia, among other countries.[7] These surveys have had much in common, mainly as a result of an emerging network among the researchers concerned. The major types of data, common to most or all of these surveys, cover the following areas:

- Firm activity and performance data: sales, employment and investment
- Innovation activity: R&D and non-R&D inputs (meaning firm-level expenditures on such activities as industrial design, market exploration and so on).
- Innovation outputs (to be discussed in more detail below)
- Sources of innovative activity or ideas; objectives of innovation
- Factors promoting innovation
- Obstacles to innovation
- Use of key technologies, in particular use of IT inputs.

On the innovation output side, an important aspect of these surveys was that while many of them began with indicators similar to those of the 'object' approach, they moved towards a more economically-oriented indicator.[8] The point of departure for most of these surveys was the idea that firms usually know, with some degree of accuracy, whether their product mix has changed or not. Certainly, they are able to identify a new product within that mix. So firms can be asked to identify numbers of new products; the resulting estimate is one potential indicator of innovation output. The fundamental objection which has been made to this is that

[7] For an overview of these surveys, 'Technological innovation indicators: experience and prospects', Science and Public Policy, Vol 19 No 6, Dec 1992, pp.24-34.

[8] Some surveys, notably that in the Netehrlands, did not seek to collect and output indicator.

products are incommensurable between industries: it makes little sense to compare the outputs of a mechanical engineering firm with those of a pharmaceuticals producer. Nevertheless, within industries, such counts may well be useful and meaningful for inter-firm comparisons. However, a simple count of the numbers of new products shares one of the primary weaknesses of patents as an indicator, namely that it gives no account of the economic significance of the innovation.

This has led to a related indicator, based on the idea that new products must actually be commercialised, and that their significance for the firms rests on the contribution which they make to revenues. A number of investigators have asked questions concerning *the proportion of sales derived from new products over a particular time period.* This is in effect an indicator of the rate at which firms replace their product mix; it is likely to vary among industries, and perhaps over time. But it does reflect both technological newness and economic significance. In Italy, for example, the 1987 survey a first questions asked for the numbers of products which were new for the firm, new for the sector in Italy, and new for the sector as a whole. It then asked a second question on numbers of products which involved "substantial improvements to existing products", and finally asked firms to '*Indicate the share of the firm's turnover in 1985 accounted for by the technologically changed products/processes covered by questions 1 and 2 and introduced in 1981-85.'*

These types of questions appeared to generate reasonably reliable answers, and generated a number of suggestive general conclusions. All of the surveys all showed that innovation has a wide industrial distribution; innovation was spread across all industries, with high-R&D industries not necessarily being the most important. Second, innovation input structures varied across industries, and this can only be captured with the types of data produced in these surveys. Thirdly, there is considerable inter-industry variation in sources and objectives of innovation.

These surveys suggested that it was possible to gather data based on samples which imply the possibility of representative views of innovation in manufacturing sectors as a whole, rather than of those companies and industries introducing significant innovations only. Secondly,

they often generated a wide variety of data on innovation inputs other than R&D. Thirdly, they often included company data on investment and performance (sales growth, employment, and so on), which opened up the possibility of analysing impacts of innovation. Finally, they often involved an *economic* indicator of innovation output, based on the contribution of innovation to turnover, which gave at least some possibilities for comparing innovation eprformance across firms and industries.

It was these studies which gave rise the the attempt to build a common European standard in this area, namely the Community Innovation Survey. We turn now to a discussion of the strengths and weaknesses of this initiative.

9. THE COMMUNITY INNOVATION SURVEY: BASIC APPROACH

In the early 1990s, the OECD (through what is now the Economic Analysis and Statistics Division) decided to attempt to synthesize the results of the various innovation surveys described above, and to develop a manual which might form the basis of a common practice in this field. A group of experts was convened, and over a period of approximately 15 months developed a consensus on a draft manual.[9]

The European Commission, in a joint action between Eurostat and the European Innovation Monitoring System (EIMS) in DG-XIII followed up the OECD initiative in 1992-93, implementing the first *Community Innovation Survey* in collaboration with Member States. CIS was an innovative action in a number of respects. Firstly, it was a large-scale attempt to collect internationally comparable direct measures of innovation outputs. Secondly, it collected data at a highly disaggregated level - firm level, in fact - and made this data available to analysts. The basic approach of the CIS is to define a technologically changed product as one in which technical characteristics or performance attributes have changed - either radically or incrementally - and then to ask firms about the proportions of their sales which flow from products which are either new or have been technologically changed over the past three years.

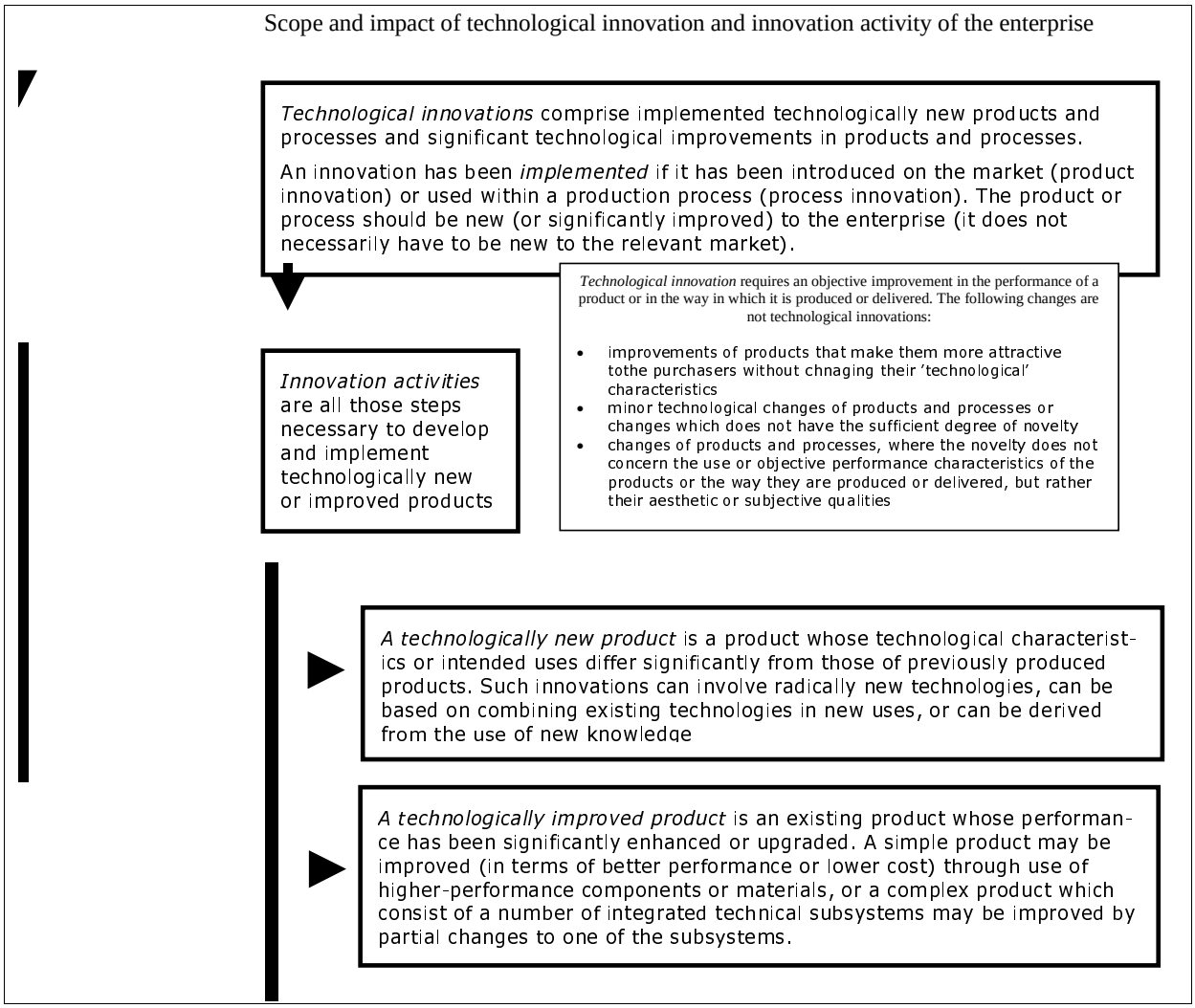
[9] Innovation Manual: Proposed Guidelines for Collecting and Interpreting Innovation Data (Oslo Manual), OECD, Directorate for Science, Technology and Industry, Paris, 1992, pp.55.

CIS developed and incorporated data on the following topics:[10]

- expenditure on activities related to the innovation of new products (R&D, training, design, market exploration, equipment acquisition and tooling-up etc). There is therefore a unique focus on non-R&D inputs to the innovation process.
- outputs of incrementally and radically changed products, and sales flowing from these products
- sources of information relevant to innovation
- R&D performance and technological collaboration
- perceptions of obstacles to innovation, and factors promoting innovation

In terms of definitions, the CIS followed the Oslo Manual in a number of crucial respects. Firstly, it focused on technological innovation, particularly in products. But it then defined different categories of change, and asked firms to assign the product range of the firm to these different categories, and to estimate the proprotions of sales which were coming from new or radically changed products, from products which had been changed in monor ways, or from unchanged products. The definitions of technological innovation currently used in CIS are as follows:

[10] For a full description of these variables, the reader should consult the European Commission document, The Community Innovation Survey - Status and Perspectives (Luxembourg 1994).



In deciding what was 'new' about an innovation, the Oslo Manual and CIS took the view that an innovation was something *new to the firm*; so when firms were asked to estimate sales from new or changed products, this meant products new to that particular firm. Of course this implies some degree of confusion the innovation of genuinely new products, or the adoption of innovations developed elsewhere. In an attempt to overcome some of these problems, firms were asked to distinguish between new product sales which emerged from products new to the firm, products new to the industry, or products which were in some sense wholly new.

10. Innovation activities and their measurement

A second feature of the Oslo Manual and of CIS was the attempt to estimate expenditures on categories of innovation activity other than R&D. Six main categories of innovation activities were identified, and the basic structure of the questions and definitions was as shown in the figure below.

Results from this ambitious attempt to gather non-R&D input data will be discussed below. But it can easily be seen that there are likely to be problems: these are complex categories, in an area where firms do not necessarily keep separate or detailed records; in practice, in the first round of the CIS, there were many firms who did not respond to the questions which were asked on this topic, and many who were clearly able to answer only in terms of broad estimates.

Resources devoted to innovation activities in 1996

Did your enterprise engage in the following innovation activities in 1996?

if yes, please estimate expenditure involved

- RESEARCH AND DEVELOPMENT OF NEW PRODUCTS AND PROCESSES (R&D)
- ACQUISITION OF MACHINERY AND EQUIPMENT LINKED TO PRODUCT AND PROCESS INNOVATIONS
- ACQUISITION OF EXTERNAL TECHNOLOGY
- INDUSTRIAL DESIGN, OTHER PRODUCTION PREPARATIONS FOR NEW PRODUCTS
- TRAINING DIRECTLY LINKED TO INNOVATIONS
- MARKET INTRODUCTION OF INNOVATIONS

TOTAL EXPENDITURE

The expenditure items should cover current (labor costs, acquisition of services, materials etc.) and capital expenditure (instruments and equipment, computer software, land and buildings). If it is not possible to estimate all expenditure items involved, please at least indicate if your enterprise has been engaged in a particular innovation activity or not.

If you have any R&D expenditure mentioned above, please indicate...

- percentage of R&D contracted out
- R&D personell in full time eqivalents in 1996
- did your enterprise engage in R&D on a continous basis (opposite to occational) between 1994 and 1996?

Research and development of products and processes (R&D) comprises creative work undertaken on a systematic basis in order to increase the stock of knowledge, and the use of this stock of knowledge to devise new applications. Construction and testing of a prototype is often the most important phase of R&D. Software development is included as well. R&D can be carried out within the enterprise or R&D services can be aquired.

Acquisition of machinery and equipment linked to product and process innovations (including integrated software) implemented by the enterprise.

Acquisition of external technology in the form of patents, non-patented inventions, licences, know-how, trademarks, drawing plans and other consultancy services (excluding R&D), related to the implementation of technological innovations, plus the acquisition of packaged software that is not classified elsewhere.

Industrial design and other production preparations for new products include plans and drawings aimed at defining procedures, technical specifications and operation features necessary to the production of technologically new products and the implementation of new processes. Design of prototypes is a part of R&D. This item also include changes in production and quality control procedures, methods and standards and associated software required to produced the technologically new or improved product or to use the technologically new or improved process. Product or process modifications needed to start production, including trial production (not included in R&D) is also included.

Training directly linked to innovations is training for the implementation of a technologically new or improved product. Expenditure for training might include acquisition of external services and expenditure for in-house training.

Market introduction of innovations includes activities in connection with the launching of a technologically new or improved product. These may include preliminary market research, market tests and launch advertising, but will exclude the building of distribution networks to market innovations.

11. CIS: Some main results

What have we learned so far from attempts to measure and map innovation? In this section we look at some of the results which have emerged from a range of studies using CIS. Here it is important to remember that the first round of CIS was very much a pilot project, and that there were many difficulties involved in the analytical use of the data. Nevertheless a wide range of studies have been carried out, mainly sponsored by the European Innovation Monitoring system, an action within DG-XIII. These studies have covered general features of innovation in Europe (input structures, output patterns, technology transfer, information flows, and employment for example), as well as a wide range of sector studies, including chemicals, pharmaceuticals, machinery and engineering, telecommunications, computing, and so on.[11]

Innovation Outputs

In this section we look essentially at results concerning two phenomena: firstly, the *pervasiveness* of innovation, and secondly the links between innovation and firms size. The first of these issues relates to a very important policy issue: is innovation something which is confined to high-tech, innovating sectors? Or does it occur across the whole economy? Does the usual policy focus on so-called 'high-tech' sectors really reflect the pattern of industrial innovation in our society?

The CIS data suggests considerable turbulence, in the sense that the product mixes of firms are subject to frequent technical change, and product mixes change dramatically over quite short time periods. But it also shows pervasive innovation across sectors.

Tables 2.2 and 2.3 show comparative data for a sub-sample of five countries within the CIS dataset; this data is drawn from a sub-project in which researchers from the countries concerned collaborated in adjusting for differences due to sampling methods, and then scaled up the data to national totals. First, what proportion of companies innovate, in the sense of introducing new products? Table 2.2. shows that the proportion of innovative companies is high; there is of course variation across sectors and countries - presumably reflecting different patterns of sectoral specialisation.

[11] For an overview, see A. Arundel and R. Garrelfs (eds) Innovation Measurement and Policies . Proceedings of the International Conference, Luxembourg May 20-21 1996, European Commission, 1997. The full range of studies can be found on the EIMS web-site at http://www.cordis.lu/eims/src/stud.htm

Table 2 .2.: Percentages of firms which had some sales of innovative products ('new to the firm' (Netherlands, Norway, Denmark, Germany)

Industry	NACE	N	NL	DK	IE	A	G
Mining, oil and gas extraction, energy and water supply	**10-14, 40-41**	[2]**26**	**31**	**39**	**na**	**na**	**14**
Food and beverages, tobacco	**15, 16**	**23**	**37**	**25**	**na**	**na**	**16**
Textiles, wearing apparel	**17-18**	**26**	**28**	**36**	**na**	**na**	**46**
Wood and wood prods, pulp and paper, publishing and printing	**20-22**	**12**	**27**	**25**	**na**	**na**	**18**
Petroleum refining, chemicals, rubber and plastic prods	**23-25**	**44**	**57**	**66**	**na**	**na**	**58**
Other non-metallic mineral prods	**26**	**29**	**44**	**45**	**na**	**na**	**26**
Basic metals	**27**	**38**	**22**	**57**	**na**	**na**	**34**
Fabricated metal prods excl machinery and equipment	**28**	**18**	**27**	**44**	**na**	**na**	**45**
Machinery for prod and use of mechanical power, machine tools	**29.1, 29.4**	[1]**34**	**47**	**39**	**na**	**na**	**77**
General purpose machinery, weapons and ammunition	**29.2, 29.6**	[1]**34**	**46**	**53**	**na**	**na**	**68**
Agricultural and forestry machinery, other special purpose machinery, domestic appliances	**29.3, 29.5, 29.7**	**71**	**46**	**73**	**na**	**na**	**85**
Office machinery and computers, radio, tele and communication	**30, 32**	**56**	**58**	**88**	**na**	**na**	**69**
Electrical machinery and apparatus	**31**	**30**	**53**	**61**	**na**	**na**	**61**
Medical, precision and optical instruments	**33**	**30**	**51**	**71**	**na**	**na**	**70**
Motor vehicles, aircraft and spacecraft	**34, 35.3**	[1]**71**	**56**	**46**	**na**	**na**	**36**
Other transport equipment (excl air and space)	**35 excl 35.3**	**12**	**21**	**25**	**na**	**na**	**34**
Furniture, other manufacturing	**36**	[1]**36**	**16**	**24**	**na**	**na**	**46**
Size classes							
10-19		**13**	**20**	**na**	**na**	**na**	**35**
20-49		**24**	**30**	**35**	**na**	**na**	**35**
50-99		**36**	**52**	**46**	**na**	**na**	**39**
100-199		**45**	**59**	**58**	**na**	**na**	**49**
200-499		**59**	**61**	**43**	**na**	**na**	**57**
>=500		**55**	**72**	**67**	**na**	**na**	**80**

In general, the proportion of firms with innovation rises with firm size, across manufacturing as a whole. But how important is change in the product mix - 'creative destruction' among products - in those firms which have introduced new products? Table 2 indicates the relative proportions of sales deriving from 'products new to the firm', introduced to the market within the last three years, among innovative firms across five countries, broken down by industry. There are two primary points to note. The first is that the proportions are high: they imply complete change in product mixes at firm level over relatively short periods. The second point is that innovation in the sense used here is relatively evenly spread across all industry groups in all of these countries.

Table 2.3: Shares of products 'new to the firm' in 1992 sales of those firms which have products new to the firm. (Netherlands, Norway, Denmark, Ireland, Austria, Germany)

Industry	NACE	N	NL	DK	IE	[2]A	G
Mining, oil and gas extraction, energy and water supply	10-14, 40-41	25	22	na	na	[1]23	36
Food and beverages, tobacco	15, 16	45	32	48	na	20	34
Textiles, wearing apparel	17-18	33	39	[1]47	na	49	43
Wood and wood prods, pulp and paper, publishing and printing	20-22	22	27	24	na	30	30
Petroleum refining, chemicals, rubber and plastic prods	23-25	27	31	27	na	32	51
Other non-metallic mineral prods	26	24	28	[1]23	na	28	31
Basic metals	27	10	15	[1]27	na	20	33
Fabricated metal prods excl machinery and equipment	28	44	28	29	na	25	42
Machinery for prod and use of mechanical power, machine tools	29.1, 29.4	[1]40	29	[1]32	na	[1]33	37
General purpose machinery, weapons and ammunition	29.2, 29.6	[1]44	46	31	na	[1]42	49
Agricultural and forestry machinery, other special purpose machinery, domestic appliances	29.3, 29.5, 29.7	64	43	34	na	34	58
Office machinery and computers, radio, tele and communication	30, 32	56	47	37	na	[1]46	77
Electrical machinery and apparatus	31	52	43	29	na	41	46
Medical, precision and optical instruments	33	56	42	38	na	[1]49	51
Motor vehicles, aircraft and spacecraft	34, 35.3	[1]31	46	[1]38	na	[1]43	60
Other transport equipment (excl air and space)	35 excl 35.3	46	36	[1]40	na	[1]10	36
Furniture, other manufacturing	36	[1]46	39	[1]41	na	50	66

It is worth noting also that, across this group of countries, proportions of sales from innovative products do not differ radically across size classes of firms. Table 2.4. shows that if we exclude the smallest size class (10-19 employees) proportions of sales from new products vary little. This suggests pervasiveness of innovation across not just across sectors, but across types of firms:

Table 2.4: Proportion of sales of products 'new to the firm', by size class

Size-classes:	NL	N	DK	IE	A	D
10-19	29.2	45.6	NA	NA	22.2	57.0
20-49	33.0	35.1	35.0	NA	29.1	48.0
50-99	33.7	36.0	31.0	NA	34.7	46.0
100-199	35.5	40.0	36.0	NA	34.5	40.0
200-499	34.0	36.5	30.0	NA	37.4	42.0
$\geq$ 500	35.5	26.3	28.0	NA	37.4	45.0

Using formal statistical methods, and covering a much wider group of countries, Calvert et al tested the link between firm size and new product sales, and showed that in only one sector (communbications) was there a significant link between innovation output and firm size.[12]

Innovation expenditures

We noted above that the CIS collected data on a range of non-R&D innovation costs, namely product design, trial production, training and tooling-up, acquisition of products and licences, market analysis and other expenditures. But it also collected data on innovation-related investments, that is purchase of capital equipment which involved acquisition of new technology through investment in new machinery and equipment.

A study by Evangelista et al asked whether, when analysing an industry, the extent or intensity of innovation expenditure was consistent across countries in Europe, or whether these levels varied across countries. The policy signficance of this question lies in the fact that if the structure of innovation inputs is similar in the same industry across Europe, then there may a common European technological level, and it may be possible to identify appropriate arenas for European action in terms of RTD support.

The study showed that innovating firms commit significant resources to innovation, ranging from 7-8% of turnover in traditional industries to 12-15% in high-tech sectors. The composition of innovation costs varies, with between 10 to 25% made up of R&D, roughly 30% comprising non-R&D expenditures, and between 40 and 60% comprising investment expenditures. The levels of innovation expenditure (measured in terms of innovation expenditures as a proportion of turnover) are very similar across European industries in different Member States. This suggests that the intensity of innovation expenditure reflects features of the industry, rather than country-specific features.[13]

In terms of the relationship between inputs and outputs, Calvert et al showed that at industry level, sales of new products are correlated both with R&D inputs, but also with the more general innovation inputs mentioned above.

[12] J. Calvert, C. Ibarra, P. Patel and K. Pavitt, Innovation Outputs in European Industry. Analysis from the CIS, EIMS Publication No 34, European Commission, 1996, p.

[13] (R. Evangelista et al) Innovation Expenditures in European Industry , Report to the European Commission, DG-XIII-C, , European Innovation Monitoring Initiative, 132 pp.

12. SUMMARISING EXPERIENCES/CRITICISMS OF CIS

While the CIS is clearly a step forward in terms of the type and volume of innovation data which is available, it is nevertheless open to a wide range of criticism. Perhaps the most important of these relates to imprecision in the definitions of innovation. The basic problem is that the CIS definitions – in terms of sales of changed products which are new to the firm concerned – give little guide to the overall quality of innovation which is occurring. It is generally unclear just how much creative activity is involved in the types of innovation outputs which CIS measures, and this is an issue, since as Arundel has pointed out, 'When we talk about a firm expending a great deal of effort on innovation, we are not only speaking of financial investments, but of the use of human capital to think, learn and solve complex problems and to produce qualitatively different types of innovations.'[14]Archibugi and Pianta have summed up the various strengths and weakensses as follows:

Table 2.4. : Comparability, strengths and weaknesses of innovation surveys

	INNOVATION SURVEYS	
	'Object approach'	*'Subject' approach*
Time series compatibility	Generally high within a given survey	Low, unless information is collected periodically and is standardised
International comparability	Low. All surveys are national in scope. Difficult to compare them because of different sample method and design	Potentially high for quantitative data if identical questionnaires and methods are used
Comparability with R&D	Low, since R&D surveys are at firm level and not at innovation level	High, since surveys allow make it possible also to collect information on input data. Both innovation and R&D surveyscollect information at firm level
Comparability with industrial statistics and national accounts	Low, beacause it is difficult or even impossible to relate the sampled innovation to the whole universe	High on quantitative data if innovation surveys can be related to the economic universe
Other advantages	- Direct measures of innovation - Provides information on technological evolution	- Provides information on all innovative activities - Wide coverage of issues - Informs on both producers and users of innovation
Other disadvantages	- Heterogenous value of individual innovations - Data biased by subjective judgement - Difficult to assess the significance and representativeness of the sample	- Does not inform on the technoogical nature of innovations - Significance and representativeness of results are tied to response rate achieved

Source: Archibugi & Pianta (1996) p. 22

13. FUTURE CHALLENGES FOR INNOVATION INDICATORS

It is obvious that innovation policy must - if it is to be effective - be based on a serious and accurate understanding of the nature and effects of innovation itself. What has recent theoretical and applied analysis told us about these issues? And what are the implications of what has been learned, firstly for policy, and secondly for the development of indicators?

[14] A.Arundel, 'Why innovation measurement matters', in Arundel and Garrelfs, op.cit, p.6.

Although modern innovation research is very wide-ranging and heterogeneous, we would argue that there are six primary developments which have reshaped both the research agenda and our understandings of innovation in its economic and social context, and which consequently have both policy implications and impacts on our needs for quantitative data. These developments are as follows:

- the emergence of *interactive models of innovation*, in which linear notions of innovation have been superseded by models which stress interactions between heterogeneous elements of innovation processes. Innovation is thus seen in terms of complex interacting ensembles of activity, rather than sequential stages dependent on prior processes of scientific discovery.
- the growth of *evolutionary analyses of economic change*, which see innovative and economic processes not as the result of optimisation and maximising decisions, but as the outcomes of economic and social selection procedures acting on highly diverse development processes in situations of extreme uncertainty and bounded rationality.
- *systems theories of innovation and knowledge creation*, which are based on the crucial insight that firms never innovate alone, but always within the context of structured relations with other firms, institutional infrastructures, networks, formal knowledge-creating institutions (such as universities or research institutes), legal and regulatory systems etc.
- *models of interactive learning*, which stress processes of interaction in knowledge creation, in which firms and networks exchange and trade information to create innovative outcomes.
- *endogenous theories of economic growth*, (which can encompass evolutionary, quasi-neo-classical and technology-gap models), which focus on the dependence of growth rates on discretionary decisions concerning investment in R&D and other knowledge-creating activities.
- *incrementalist approaches to innovation*, based on awareness of the fact that innovation is widely spread: it does not consist simply of radical breakthroughs in high-tech manufacturing industries, but is often small scale and spread throughout manufacturing and the services sector (which - in quantitative terms - is far of greater importance to output and employment than manufacturing).

A basic issue in the development of innovation statistics, therefore, is that recent developments in theories of technological change and innovation, and in innovation policy, have outrun the ability of the available statistical material to provide either empirical evidence for theory, or adequate empirical grounding for policy. We therefore face two types of challenge for the future, with respect to innovation measurement. The first is to improve our existing measures. The second is to develop new indicators for new areas of research and policy analysis.

III. R&D DATA AND R&D INDICATORS

Tore Sandven

This chapter deals with perhaps the most frequently used indicator of the innovative process, namely R&D (research and development) activity. The main problem which is emphasized in this chapter is the need for care when making international comparisons of R&D effort across countries. As we shall see, there are some important difficulties in using some of the most familiar R&D indicators.

The key OECD document for the collection of R&D statistics is the *Standard Practice for Surveys of Research and Experimental Development*, better known as the *Frascati Manual*. The first edition was the result of an OECD meeting of national experts on R&D statistics in Frascati, Italy, in 1963. The current version of the manual, the *Frascati Manual 1993*, is the fifth edition.

The *Frascati Manual* defines R&D as comprising both the production of new knowledge and new practical applications of knowledge: 'Research and experimental development (R&D) comprise creative work undertaken on a systematic basis in order to increase the stock of knowledge, including knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications' (*Frascati Manual 1993*, OECD: Paris, 1994, p. 29). We note that the *Frascati Manual* explicitly uses the term *experimental development* for the D in R&D, not simply *development*.

R&D is conceived as covering three different kinds of activities: *basic research*, *applied research* and *experimental development*. The *Frascati Manual* gives the following definitions: '*Basic research* is experimental or theoretical work undertaken primarily to acquire new knowledge of the underlying foundation of phenomena and observable facts, without any particular application or use in view. *Applied research* is also original investigation undertaken in order to acquire new knowledge. It is, however, directed primarily towards a specific practical aim or objective. *Experimental development* is systematic work, drawing on existing knowledge gained from research and/or practical experience, that is directed to producing new materials, products or devices, to installing new processes, systems and services, or to improving substantially those already produced or installed' (p. 29).

It may often be difficult to draw the dividing line between what should be counted as R&D and what should be excluded. The crucial question here is whether the activity is aimed at producing *new* knowledge or devising *new* applications of knowledge: 'The basic criterion for distinguishing R&D from related activities is the presence in R&D of an appreciable element of novelty and the resolution of scientific and/or technological uncertainty, i.e. when the solution to a problem is not readily apparent to someone familiar with the basic stock of commonly used knowledge and techniques in the area concerned' (p. 33). Education and training shall thus in general *not* be counted as R&D, even if often closely related to R&D, for instance university education. There are also many other activities with a scientific and technological base which are to be kept distinct from R&D. These include such industrial activities related to innovation as acquisition of products and licences, product design, trial production, training and tooling up, and market analysis, as well as the acquisition of equipment and machinery related to product or process innovations. In the Community Innovation Survey (CIS) collects data on the costs of the above industrial activities related to innovations. These costs are included in the broader category 'innovation costs', which includes R&D costs as well as these innovation costs not counted as R&D.

Basically, there are two kinds of data on R&D activities which are collected, namely *expenditures* on R&D and R&D *personnel*. Persons engaged in R&D are classified either by occupation or by formal qualification. The data are normally collected on a *yearly* basis: so much money spent on R&D during a particular year, so many man years, in full time equivalents, used on R&D during a year.

R&D is classified according to several criteria.[1] There is, first, the distinction between basic research, applied research and development. One may classify by sector of performance: business enterprise, government, higher education and private non-profit. Using the same sectors, one also distinguishes between sector of performance and sources of finance; for the sources of finance, one includes funds from abroad in addition to the other sectors. For business enterprise R&D, one also classifies by industry. R&D expenditures are also classified as current expenditures and capital expenditures, etc.

[1] See, for instance, OECD, *Basic Science and Technology Statistics*, Paris: OECD, for instance 1995.

For purposes of comparison, for instance across firms or industries or countries, simply reporting gross magnitudes, such as total expenditures on R&D or total number of man years, will often not be very meaningful. Instead, one reports some version of *R&D intensities*, where the R&D activities in question are related to some measure of total activities. The R&D intensity concept most frequently met with is total R&D expenditures as a proportion of total production, for instance R&D expenditures as a percentage of value added. However, one may also look at R&D expenditures per employee (in the case of for instance individual firms or industries or also the total business enterprise sector) or per inhabitant (in the case of a region or the nation as a whole). Alternatively, one may relate R&D measured in man years to total man years worked in a given firm or industry or economy. The point about R&D intensity is that the effort in terms of R&D is measured against the total activities or effort or production of the unit in question.

1. R&D activities: an input indicator

One should keep in mind that measures of R&D activities are *input* or *effort* measures. They say something about how much effort, how much resources, have been put into an explicit effort at creating new knowledge and develop new products and processes. They do not say anything about how much innovation *output* comes out of this effort in terms of new products and processes and more generally improved performance. The relationship between R&D effort and innovation output may vary, for instance across countries, for a number of reasons. For instance, the quality of the research and development work done may simply not be the same in all countries. The nature of the relationship may also depend on the organization of business enterprises, for instance on how well R&D activities are integrated with other activities of the enterprises. Also important, not least for the diffusion of innovations, is the nature of the relationships among firms and between firms and other organizations like research institutions, universities, public support institutions, etc.

2. The question of undercounting of small firm R&D

Research done by Alfred Kleinknecht and associates in the Netherlands indicates that there maybe problems concerning small-firm R&D in national surveys of R&D expenditures.[2] The reason for this is thought to be that in small firms R&D is less visible than in small firms.

[2] See for instance Alfred Kleinknecht and Jeroen O.N. Reijnen, 'More Evidence on the Undercounting of Small Firm R&D,' *Research Policy*, Volume 20, Number 6, December 1991, pp. 579-587.

Large firms very often have separate R&D departments in addition to separate R&D budgets. Small firms seldom have separate R&D departments, and often not even separate R&D budgets. Even if they do engage in R&D activities, they may be less likely to think of this as R&D. Much of the R&D which they do is probably also *ad hoc* and informal, rather than carried on as a separate activity on a permanent basis. Also, probably almost all of this R&D is D rather than R.

This raises the broader question of the relationship between R&D which is performed explicitly and self-consciously as a special kind of activity on a permanent basis, on the one hand, and R&D activity which is more *ad hoc* and informal, embedded in the ongoing productive activities of the firms, a response to problems and questions which emerge in the course of the daily activities which make up the production process, on the other. It seems highly likely that the former type of R&D activity will have a higher probability of being captured through surveys of R&D expenditures than the latter, which thus is much more likely to be undercounted.

Moreover, to concentrate on the explicit, formal, separate R&D activities and largely ignore more formal and ad hoc R&D activities would seem to have a certain affinity with the so-called 'linear model of innovation,' a conception of the innovation process which was dominant up to the 1980s.[3] In this conception, the innovation process was represented as a relatively well-defined sequence in time, which originated in research and then went through product development and production to eventual commercialization. Conversely, in the type of conception of the innovation process which seems generally accepted today, often referred to as an interactive model, it is a basic point that R&D is not confined exclusively or not necessarily even primarily to the origin of the process, but is performed in relation to questions and problems at *all* stages of the innovation process, from market analyses through design, testing, production, distribution and marketing, and then again through subsequent improvements of the product. With this kind of conception, one should be much more concerned with also getting registered the R&D of a more informal, *ad hoc* character, i.e. in addition to the R&D explicitly acknowledged as such by the firms themselves.

[3] For an exposition and critique of the linear model of innovation, the standard reference is Stephen J. Kline and Nathan Rosenberg, 'An Overview of Innovation,' in Ralph Landau and Nathan Rosenberg, eds., *The Positive Sum Strategy: Harnessing Technology for Economic Growth*, Washington, D.C.: The National Academy Press, 1986.

These issues also connects to the issue of what kind of general view one has of productive activities and of human action more generally, of whether one has a an exclusively instrumental view of action or whether one has more of a process orientation to action, seeing instrumental action as embedded within practices which to a certain extent have a logic of their own. The traditional approach is highly instrumental, seeing action as the carrying out of decisions, which in their turn are taken in order to bring about certain goals or solve certain problems. With this view, one is likely to concentrate on actions which have been planned in advance, which there are formal decisions on, which are formalized through budgets and department structures. This is an orientation which seems to go well with the 'linear model.' If one has a process orientation, on the other hand, one focuses less on decisions, and is more interested in understanding the actual dynamics of practices and processes, of how the participants at different levels are involved in the action, interaction and 'conversations' which make up the processes, of how problems and issues and orientations all the time emerge from this involvement in practices and processes which in part have their own logic and momentum.[4] It seems logical that this latter approach should be far more attentive to the R&D of a more informal and *ad hoc* character than the traditional, instrumental approach.

This discussion should be highly relevant to central issues concerning the distinction between radical and incremental innovations. The traditional view tends very much to focus on the radical innovations and to ignore the incremental innovations. However, incremental innovations, the gradual improvements in products and processes occurring largely as the participants try to deal with the day to day tasks and issues in their work, are also very important, and should be far more visible in the alternative, process-oriented approach than in the traditional, decision-oriented approach.

These issues also have relevance to the distinction between R&D and innovation activities which are not to be counted as R&D.

[4] For a very interesting general discussion, see Michael J. Piore, Richard K. Lester, Fred M. Kofman and Kamal M. Malek, 'The Organization of Product Development,' *Industrial and Corporate Change*, Volume 3, Number 2, 1994, pp. 405-434, which distinguishes between an approach which is analytical and problem-oriented, which is the dominant approach to design and development, and an alternative approach which is interpretative and process-oriented.

3. The comparability of different economies

Often R&D expenditures of different countries or national economies are compared. These comparisons must, of course, be based on some version of R&D *intensities*. In the same manner, one may also compare different *regional* economies, where the regions may be regions *within* individual countries or regions comprising two or more countries or regions crosscutting national boundaries. However, the country or national economy is by far the most common unit for these comparisons, and the basis for all OECD statistics.

By far the most common R&D intensity measure used here is total R&D expenditures in a country in a given year as a proportion of GDP. In OECD statistics total R&D expenditures of a country are often referred to as GERD, for *Gross domestic expenditures on R&D*. The R&D intensity at the country level may thus be written GERD/GDP. This measure is often used in connection with policy recommendations. Typically, the R&D expenditures of a given country are said to be inadequate by reference to a higher ratio of GERD/GDP in certain other countries.

However, there is a question if this kind of direct comparison is altogether meaningful, or if other factors should be taken into account to make the comparisons more relevant. We shall now consider two such factors, the *size of the economy* and the *industrial structure* of the countries being compared.

4.Controlling for size of economy

One problem with these kinds of comparisons is that it may be unreasonable to compare directly economies of substantially different sizes, for instance small and large economies. The reason is that there is a general tendency for GERD/GDP, or R&D intensity, to increase with increasing size of the economy (as measured by GDP). This is argued, for instance, by J.A.D. Holbrook in an article in *Science and Public Policy*.[5] Holbrook sees this as an effect of *scale*. We would thus simply expect that a larger economy should have a higher R&D intensity than a smaller economy. Should they in fact have similar R&D intensities, this could then be said to represent a stronger R&D *performance* in the smaller than in the larger economy.

[5] J.A.D. Holbrook, 'The influence of scale effects on international comparisons of R&D expenditures', *Science and Public Policy*, Volume 18, number 4, August 1991, pp. 259-262.

The implication is that one should preferably compare economies of similar size. One should be cautious when comparing economies of different sizes, taking this difference into account. One way of taking this difference into account is by constructing a measure which adjusts for economy size. This could, for instance, be done by means of regression analysis. If one has a data for both GERD and GDP for several countries in a given year, one would then regress R&D intensity (GERD/GDP) on GDP. (It might here be reasonable to transform the often highly skewed GDP variable, for instance through a log transformation.) Provided that one actually finds a relationship between size of economy and R&D intensity, one could then calculate the *predicted* GERD/GDP scores, conditional on the GDP scores (which may or may not have been transformed). These predicted scores should then be subtracted from the actually observed GERD/GDP scores. The resulting *residuals* would then be the indicator which adjusts national R&D intensities (GERD/GDP) for differences in economy size, as measured by GDP. Thus, for instance, a *small* economy with an *average* GERD/GDP would get a relatively *high* score on the R&D intensity adjusted for size of economy indicator, while, conversely, a *large* economy with an average GERD/GDP would get a relatively *low* score on the adjusted indicator (again provided that the regression analysis actually detects a non-trivial positive relationship between size of economy and GERD/GDP).

5. Controlling for industrial structure

Another factor which makes a direct comparison of GERD/GDP across countries problematic is the difference across countries in industrial structure. One should thus also take this difference into account when comparing R&D expenditures across countries. This is closely connected to the issue of adjusting for size of economy, because industrial structure tends to vary systematically with size of economy, in a sense to be explained below. In fact, to the extent that there is a tendency for GERD/GDP to increase with increasing economy size, this relationship partly reflects, or is mediated through, a relationship between economy size and industrial structure.

The point about taking into account industrial structure relates in a direct way only to R&D expenditures in the *business enterprise sector*, or BERD. These are expenditures on R&D performed by business enterprises themselves or *for* business enterprises by other institutions, irrespective of the sources of finance. The analysis of the relationship between R&D intensity

and industrial structure should be performed for business enterprise R&D expenditures only, then one could analyse the relationship between business enterprise R&D expenditures and other R&D expenditures. In any case, the share of total business enterprise expenditures on R&D (total BERD) in total R&D expenditures (total GERD) is quite large in most countries. Besides, when one is interested in innovation, one is often particularly interested in what goes on in or in relation to the business enterprise sector.

Thus, in principle the analysis of the relationship between industrial structure and R&D intensity should be performed on total expenditures on R&D in the business enterprise sector. However, because of problems concerning the availability of R&D data for activities outside of the manufacturing, one must in practice restrict the analysis to R&D expenditures in the *manufacturing* industries.

This means that in the following we will discuss comparisons across countries of R&D intensity in the manufacturing sector as a whole. Total R&D expenditures in the manufacturing sector are thus to be expressed as a proportion of total production in the manufacturing sector. As a measure of total production in the manufacturing sector we could use total value added in manufacturing, which is what in the manufacturing sector corresponds to GDP for the economy as a whole (GDP is value added for the whole economy).

The point about controlling for industrial structure when assessing the R&D intensity in the manufacturing sector (and, ideally, in the economy as a whole), relates to two basic facts about R&D expenditures and industrial structures. On the one hand, R&D intensity varies enormously across industries. On the other hand, industrial structure varies substantially across countries. One country may have a substantial share of its production in industries with high R&D intensity, while another may have a much smaller share of its production in industries with high R&D intensity. In a sense, it would then be misleading simply to compare R&D intensity in manufacturing in the two countries, because from knowledge of the industrial structure of the two countries we would expect the former country to have a higher R&D intensity in manufacturing than the latter. Even if the former country had a substantially higher total manufacturing R&D intensity than the latter, the latter might perform just as well (indeed, even better) in terms of R&D intensity as the former *inside each individual industry*. Expressed differently, R&D intensity in the manufacturing sector as a whole may be seen as

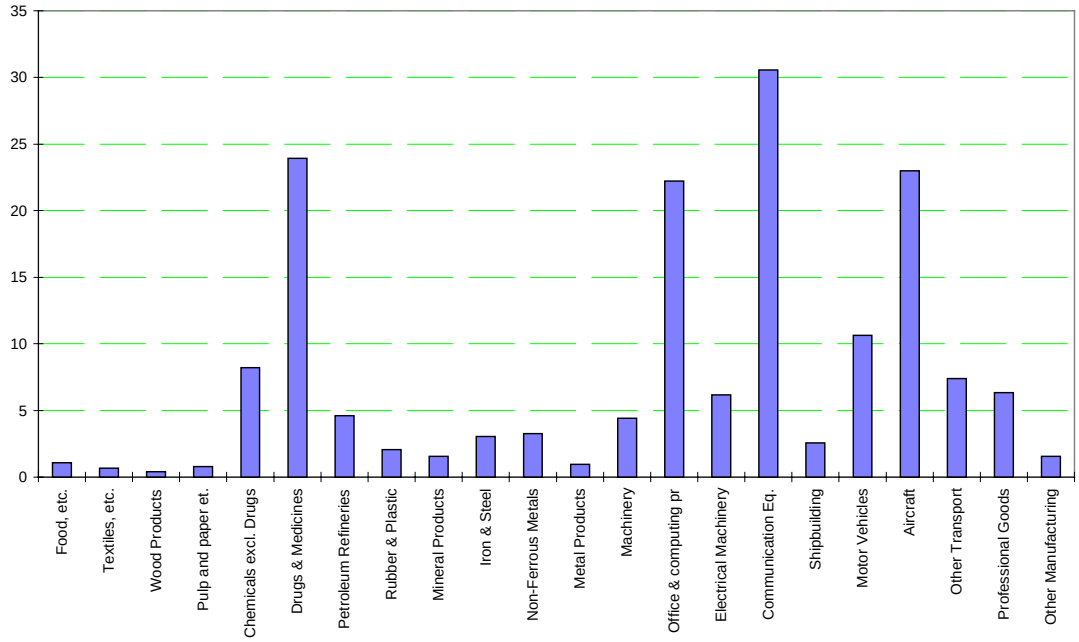
the result of two different components: on the one hand a component which reflects the industrial structure of the country in question, on the other hand a component which expresses how well the country typically performs in terms of R&D intensity inside each individual industry. Controlling for industrial structure would thus mean to find a measure of R&D intensity in manufacturing which takes into account which R&D intensity we would expect simply from knowledge of the industrial structure, or, alternatively, which expresses how well the country typically performs in terms of R&D intensity inside each individual industry.

In the following discussion the points will be illustrated by data on R&D intensity and industrial structure in the manufacturing sector in 1991 for 13 OECD countries: Australia, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Sweden, the UK and the USA.[6] The manufacturing sector is here divided into 22 industries, and in each of the countries we have data for R&D expenditures and value added for each of these industries.

The point about the variation in R&D intensity across industries is illustrated in Figure #, below. The figure shows the *median* R&D intensity across all the 13 countries for all 22 industries.

[6] For all countries apart from Norway the data are from the OECD STAN and ANBERD databases. For Norway we use data from Statistics Norway; this should be fully compatible with the OECD data and will probably soon be included in STAN/ANBERD.

Figure 3.1. . Median R&D intensity for each industry across 13 countries, 1991.



The median is preferred to the mean because in a couple of industries there are one or two extreme outlier values which make the mean misleading as a measure of the typical.

We immediately see that the variation across industries is very great. In the most R&D intensive industries, R&D intensity is typically more than 20 per cent, while in several of the traditional industries, often accounting for a large share of total production, it is typically less than 2 per cent.

The point about the variation in industrial structures is seen by comparing Figure # and Figure #, below, representing Japan and Norway, respectively. These countries are chosen because they are very different in this respect.

The charts are scatterplots, where each observation represents one industry. Along the y-axis are the *median* R&D intensity (across the 13 countries) for each industry. Along the x-axis we have each industry's share of manufacturing value added.

Figure 3.2.. Median R&D intensity across all countries for each industry, per cent, y-axis, and share of total manufacturing value added, per cent, x-axis. Japan, 1991.

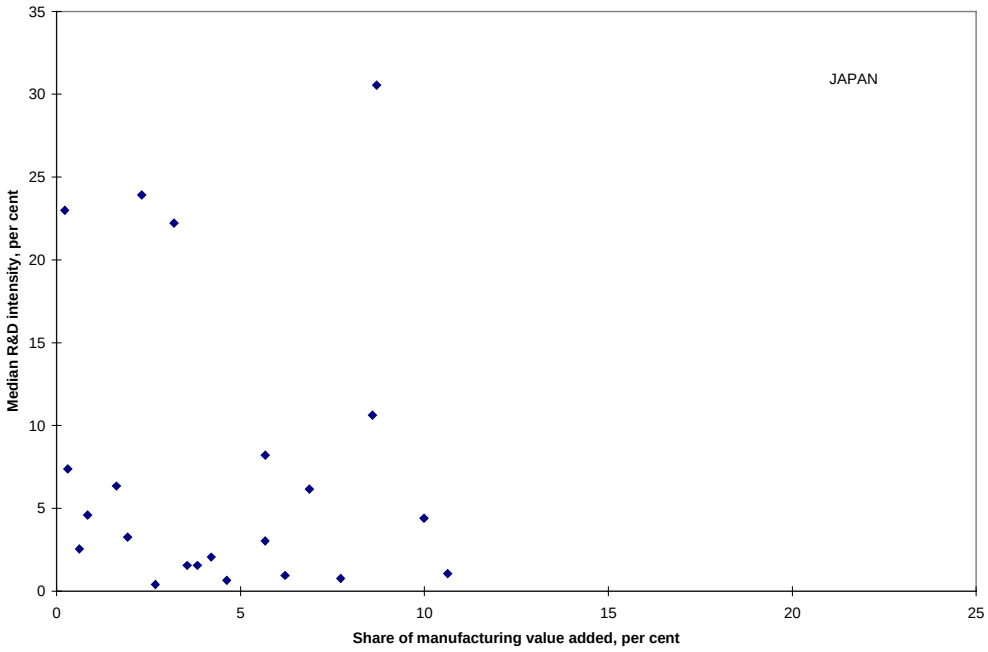
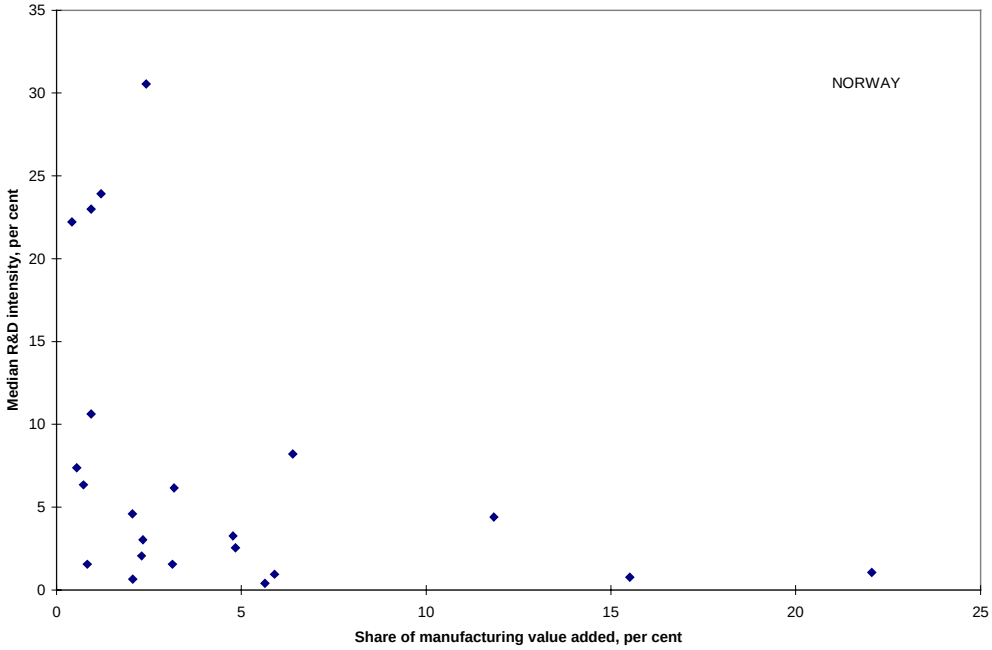


Figure 3.3. Median R&D intensity across all countries for each industry, per cent, y-axis, and share of total manufacturing value added, per cent, x-axis. Norway, 1991.



Since the R&D intensities in question are the *median* R&D intensity across all countries for each industry, each industry's value along the y-axis is the same in the two figures.

Comparing the two figures, we see that for Norway the industries tend to lie much closer to the two axes than what is the case for Japan. This means that for Norway it is generally the case that the industries which typically have high R&D intensity account for a quite small share of manufacturing production, while the industries which account for large shares of total production typically have low R&D intensity. This is not true to the same extent for Japan. Thus, from knowledge of the industrial structure of the two countries, we would expect Japan to have a considerably higher R&D intensity in manufacturing than Norway (which is actually also the case, Japan having an R&D intensity in manufacturing of 7.1 per cent in 1991, while the corresponding figure for Norway is 4.7 per cent).

How can we measure the *expected* R&D intensity conditional on the industrial structure of each country? First we define a measure of the *typical* R&D intensity of each industry. We choose here simply to use the *median* R&D intensity across the 13 countries (preferred to the mean because of a couple of extreme values, as explained above). We then ask how high R&D intensity in manufacturing each country would have had, *if* in each industry it had the typical *median* R&D intensity, and given the industrial structure which it actually has. This may be written $\sum_{i=1}^{n} \bar{I}_i \cdot w_i$, where $\bar{I}_i$ is the median R&D intensity of industry *i* and $w_i = \frac{VA_i}{VA_t}$, where VA_i is value added of industry *i* and VA_t is value added in manufacturing is a whole. We may call this the industrial structure component of R&D intensity in manufacturing as a whole. It is the weighted average across all industries of the *median* R&D intensity values for each industry, where the weights are defined by the share of total manufacturing value added accounted for by each industry in the country in question.

For a measure of R&D intensity in manufacturing which controls for industrial structure we may simply *subtract* this industrial structure component value from the actual R&D intensity value. We take the actual R&D intensity in manufacturing and subtract the value we would have expected given the industrial structure. This is equivalent to answering the question of how far above or below the median R&D intensity the country on *weighted average* lies in each individual industry, where the weights again are defined by the share of total manufacturing value added accounted for by each industry in the country in question. This we may write as $\sum_{i=1}^{n} \left(I_i - \bar{I}_i\right) \cdot w_i$, where I_i is the R&D intensity in industry *i* in the country in question. We might call this the *R&D performance* component of the R&D intensity in

manufacturing in the country in question. R&D intensity in manufacturing thus becomes the sum of two components: the industrial structure component and the R&D performance component.

Let us see how this looks for our 1991 data. R&D intensities in manufacturing are as shown in Table 3.1, below.

Table 3.1. R&D intensities in the manufacturing sector, per cent, 1991.

Sweden	9.6
USA	8.6
Japan	7.1
France	6.6
UK	6.2
Germany	6.0
Finland	5.8
Netherlands	4.9
Norway	4.7
Denmark	4.3
Canada	3.6
Italy	3.2
Australia	2.6
Mean	5.6
St. dev	2.0

We then get the following industrial structure components, i.e. the R&D intensities in manufacturing which we would expect from knowledge of the industrial structure:

Table 3.2. Industrial structure component, 1991.

Japan	7.1
USA	6.9
Germany	6.7
Netherlands	6.5
UK	6.5
France	6.0
Canada	5.6
Sweden	5.5
Italy	4.4
Australia	4.1
Denmark	4.1
Finland	3.9
Norway	3.8

We may note here that there is a quite clear tendency for the large economies to have high industrial structure component values and vice versa for the small economies.

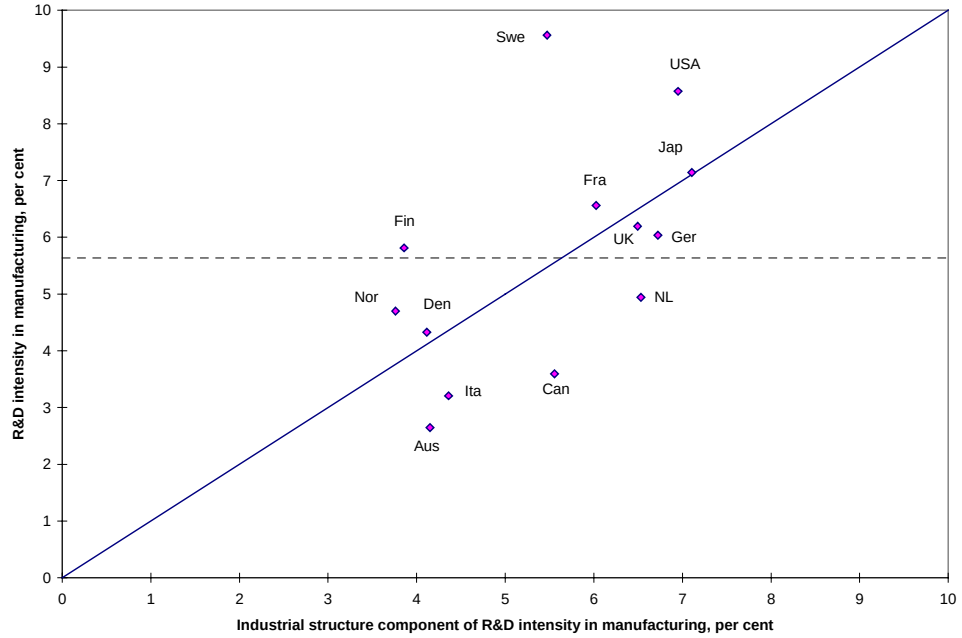
Subtracting these industrial structure component values from the R&D intensity values, we get the R&D performance component values, where R&D intensity in manufacturing is controlled for industrial structure.

Table 3. Average R&D performance: R&D intensity in manufacturing adjusted for industrial structure, 1991.

Sweden	4.1
Finland	2.0
USA	1.6
Norway	0.9
France	0.5
Denmark	0.2
Japan	0.0
UK	-0.3
Germany	-0.7
Italy	-1.2
Australia	-1.5
Netherlands	-1.6
Canada	-2.0

This adjustment is shown graphically in Figure #, below, where the industrial structure component is depicted along the along the x-axis and the actual R&D intensity in manufacturing along the y-axis. The dotted line is the mean of R&D intensity in manufacturing across all countries while the solid line is a 45 degrees line.

Figure 3.4. Controlling for industrial structure. Industrial structure component (x-axis) and R&D intensity in manufacturing (y-axis), 1991.



When we simply compare R&D intensity in manufacturing across countries we may say that we measure each country against the simple mean of the distribution, represented by the horizontal dotted line. We look at the vertical distance to this line. When we control for industrial structure, however, we measure the R&D intensity of each country against the R&D intensity we would expect given knowledge of the industrial structure, represented by the solid 45 degrees line. The average R&D performance values thus represent the vertical distance from the actual R&D intensity values to the 45 degrees line.

An alternative here to simply use the 45 degrees line as the expected R&D intensity given industrial structure would be to use the *predicted* values from a *regression* of R&D intensity on the industrial structure component, and then use the *residuals* from this regression as the measure of R&D intensity adjusted for industrial structure. In this particular case it would not make much difference which of the two methods one chose, as the regression line turns out to run quite close to the 45 degrees line. However, using the regression residuals method might be preferable when we want to adjust the R&D intensity of the whole national economy, i.e. total GERD/GDP, for industrial structure. It would also be preferable if one wanted to control for other variables in addition to industrial structure at the same time, for instance both industrial structure and size of economy.

6. Discussion of the idea of controlling for industrial structure

We have seen that the R&D intensity in manufacturing as a whole in a country may be understood as the sum of two distinct components, one expressing the industrial structure of the country and the other how well the country on average performs in terms of R&D intensity inside the individual industries. Above we have treated this latter component as a measure of R&D performance, claiming that it is misleading simply to compare the R&D intensity in manufacturing in countries with very different industrial structures and that one must take this difference into account when comparing R&D efforts.

From a different perspective, however, one would rather choose the *structure component* as an indicator of performance in relation to innovativeness and competence, the sophistication of production, etc. This will be so if one thinks that it is important for a country to engage substantially in the type of production characterized by high R&D intensity, to restructure the

economy towards the high R&D intensity industries. For instance, Charles Edquist and Bengt-Åke Lundvall adopt this perspective in an analysis of the Danish and Swedish systems of innovation.[7] Discussing the *performance* of these innovation systems, they find that 'both Denmark and Sweden have a relatively weak position in R&D-intensive products.'[8] They note that this is not so surprising in the Danish case, given Denmark's 'weak R&D effort.' However, noting Sweden's 'very substantial investments in R&D,' as well as 'its high number of patents per million inhabitants in the United States, and its strong multinationals in engineering', they find it remarkable that Sweden 'has been so slow in absorbing R&D-intensive products.'[9] One of their main conclusions is that 'the average low-R&D character of Swedish production is a severe problem for the Swedish system of technological change.'[10] Here they very clearly distinguish between an effort component and a structure component: in spite of a very substantial R&D effort, Sweden has a 'low-R&D *character of production*.' An indicator they explicitly use for this structural dimension is the share of production (and exports) accounted for by industries defined as having high R&D intensity. The structure component used in the present paper is a more generalized representation of this idea (of course, the question of exports is not treated here). Indeed, we have seen that while the R&D effort inside each industry in Sweden generally is very strong (the average R&D performance component is very high), the industrial structure as such, holding everything else equal, indicates a less than average R&D intensity in manufacturing (the structure component is not particularly high). It is this structural dimension which is one of the main issues Edquist and Lundvall emphasize in their discussion of the *performance* of the Danish and Swedish innovation systems.

From an alternative or even opposite perspective, the dimension of performance which one has in mind would be one which the *average R&D performance component*, rather than the *structure component*, says something about. In this perspective the industrial structure of the country in question is taken as given, and then one asks how well the country performs in terms of R&D effort given the industrial structure that it actually has. This is the perspective

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[7] Charles Edquist and Bengt-Åke Lundvall, 'Comparing the Danish and Swedish Systems of Innovation', in Richard R. Nelson (ed.), *National Innovation Systems. A Comparative Analysis*, New York: Oxford University Press, 1993, pp. 265-298.

[8] ibid., p. 287.

[9] ibid.

[10] ibid., p. 290.

underlying, for instance, OECD's 'STIBERD' indicator.[11] This perspective may be *opposite* from the one just discussed, in that one explicitly holds the industrial structure in question to be by and large rational, given the resources and preconditions of the country. But the two perspectives do not necessarily preclude one another. One may believe that a given country *should* change its industrial structure in the direction of a higher share of production accounted for by high R&D intensity industries, and still be interested in how well the country on average performs in terms of R&D expenditures given the industrial structure it actually has at the present. Thus, these perspectives may also be complementary.

More generally, the question of whether a measure of how well a country performs in terms of R&D effort should control R&D intensity for industrial structure is closely connected to the idea one has of what kind of industrial structure the country in question should have. If one thinks that the industrial structure of the country in question is by and large rational, at least for the time being, given the resources that the country has, it makes sense to take the industrial structure as given and control for industrial structure when one compares R&D intensities across countries. On the other hand, if one, like Edquist and Lundvall, is concerned about the industrial structure itself and thinks that the share of R&D intensive production is too low and accordingly that the industrial structure should be changed so that the share of R&D intensive production is substantially increased, then it is far less reasonable to take the industrial structure as given and control for industrial structure when assessing R&D performance. Then it would rather be more reasonable to concentrate on the *structure component* as a measure of performance. Of course, a concern about industrial structure is not incompatible with a concern about how the country actually performs inside the industries that it actually has. One may for instance say that the structure component is low, and this is bad, but the average R&D performance component is high, and this is good, even if the structure component is the more important of the two.

In conclusion, in assessing R&D performance, one should perhaps always consider both components. The relative importance which one attaches to each of them would then depend on one's position on the industrial structure issue.

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[11] Cf. *Manufacturing Performance: A Scoreboard of Indicators*, OECD Documents, Paris: OECD, 1994, pp. 51-57.

7. Taking account of the distribution of R&D expenditures across industries

The average R&D performance component adjusts R&D intensity in manufacturing for industrial structure in a quite straightforward manner. As we said, it is in essence a residual. The *structure component* says how high R&D intensity in manufacturing we would have expected in a given country *given* its industrial structure and *if* in each industry it had the *typical* (median) R&D intensity. The *average R&D performance component* is simply the difference between the actual R&D intensity of the country and its structure component. If this difference is positive, the R&D intensity inside the individual industries must on average have been higher than the typical R&D intensity, and vice versa if the difference is negative. Thus, the average R&D performance component seems to adjust R&D intensity in manufacturing for industrial structure in a quite understandable and reasonable way.

However, if R&D intensity inside individual industries is to be considered from the point of view of *performance* relative to innovation, etc., there is another aspect, in addition to adjusting for industrial structure in the above way, which should be taken into account. A high average R&D performance component value means that on *weighted* average the country in question has an R&D intensity inside the individual industries which is substantially higher than the typical. However, as applies to all averages, even weighted ones, this average may be an average of very different values. Thus, the average R&D performance component does not take into account the *distribution* of R&D expenditures across industries. For instance, a high industry component value may express particularly high R&D intensities in a few high R&D intensity industries which together account for a modest share of total manufacturing production in the country in question, while industries which together account for the major share of manufacturing production have quite low R&D intensities compared to other countries. If the distribution of R&D resources across industries in a country is very skewed, i.e. substantially more skewed than what is normal, only adjusting for industrial structure as does the average R&D performance component will not give an accurate picture of how well the industries in a given country in general perform in terms of R&D intensity. Thus, if we want a measure of how well the industries in a country in general perform in terms of R&D intensity, we should take into account *both* the industrial structure *and* the distribution of R&D expenditures across industries. The average R&D performance component takes account only of industrial structure, not of the distribution of R&D expenditures across industries.

The main point here is that an indicator which was to take into account or adjust for the distribution of R&D resources across industries would have to presuppose some idea of what a rational distribution of R&D resources would look like, to have something to measure the actual distribution against. Given the very systematic pattern of differences in R&D intensity, there is no rationale for using as a measuring rod some notion of an equal distribution of R&D resources across industries, for instance where R&D intensity was the same in all industries.

A likely candidate for a standard for a rational distribution of R&D resources across industries would simply be to take the profile of R&D intensities across industries which we typically observe, for instance defined as a median value for each industry across a number of countries, as above. Given total R&D expenditures in all industries, one could find out what distribution of these expenditures across industries would correspond to the typical profile, and one could then measure the actual deviation from this model profile through some version of the sum of deviations or the average deviation or the standard deviation or the chi square of the actual expenditures from what this typical profile would imply.

Alternatively one might say that the distribution of R&D resources which one typically observes today is *not* a rational one. Specifically, a quite common position seems to be that R&D resources generally are too heavily concentrated in the high R&D intensity industries, and that it would be rational to reallocate some of these resources towards the low R&D intensity industries. An approach based on the position that the typical distribution is too skewed would then have to face the challenge of specifying another distribution which could qualify as a standard to measure actual distributions against.

If one has an indicator which takes account of the distribution of R&D expenditures across industries, one will always have to assume some kind of ideal rational distribution. If one does not do this explicitly, it will nevertheless be implicit in the indicator. A case in point is the STIBERD indicator of the OECD, referred to above. In the presentation and description of the indicator the OECD does not make a clear distinction between controlling for industrial structure and controlling for the distribution of R&D expenditures across industries, giving the impression that the indicator is supposed to do both at the same time. However, it can be shown that STIBERD does *not* take industrial structure into account, but only the distribution of R&D expenditures across industries. Moreover, the way the indicator works is that its value increases the more R&D resources are allocated towards the industries which typically have

low R&D intensities. In fact, the indicator is extreme in favouring an allocation towards the normally low R&D intensity industries, in the sense that, given total R&D expenditures, it reaches its maximum when the allocation of R&D resources across industries is as far from the normal as possible, namely when *all* R&D expenditures are concentrated in the industry which typically has the lowest R&D intensity.

Thus, while the way we have controlled for industrial structure is quite straightforward, in effect only taking the residual from the value we would have expected given the industrial structure, adjusting for the distribution of R&D expenditures across industries raises more difficult problems.

9. Distribution of R&D expenditures inside individual industries

This issue of the distribution of R&D expenditures is even more difficult and important, because we meet it again as a problem of the distribution of R&D expenditures across firms within the same industry. The R&D intensity for each national industry is simply an average across a multitude of firms, or more precisely a *weighted* average, where total R&D expenditures of an industry is simply divided by total production. These averages hide substantial variation *inside* each industry, and the distributions are moreover in general highly skewed. The nature of these distributions is likely to be of importance in explaining innovation performance.[12] Again, there is a challenge here to develop good indicators of the distribution of R&D expenditures across firms within individual industries. In any case, one should take into account this distribution of R&D resources, both across industries and across firms in the same industry, even if one may find it difficult to find good indicators which adequately expresses this distribution, or rather, which adequately expresses how rational this distribution is in terms of implications for performance. There may also be other classifications besides industry across which it may be interesting to look at the distribution of R&D efforts, for instance across different size classes of firms.

10. Indirect R&D and Input-Output Analysis

R&D is normally registered according to where it is performed. For instance, this is typically the case when R&D is classified by industry: the R&D of a given industry is the R&D

[12] See Kirsty Hughes, 'The Interpretation and Measurement of R&D intensity – A Note,' *Research Policy*, Volume 17, 1988, pp. 301-307.

performed in this industry, or directly on behalf of firms in the industry. Our assumption is that this R&D will improve in some way or another the productivity of the industry which performs the R&D (or at least of those firms in the industry who perform the R&D). However, the R&D performed in the industry may be said to be incorporated in the products which the industry sells. These products are often, especially in the case of investment goods like machines and equipment, bought by firms in other industries. Presumably, the R&D performed in the production of these investment goods will enhance the productivity of these investment goods, too. Thus, they must also be assumed to improve the productivity of the firms who buy the investment goods. In a sense, the firms who buy products from firms who perform R&D and use these products as inputs to their own production process may be said to use R&D indirectly. Thus, even if we have data on R&D performance, these do not tell us everything about who are the beneficiaries of the R&D performed

In this way, we may think of inter-industry technology flows based on the R&D performed in each industry, where the total R&D performed in an industry may be thought of as incorporated in the products which it sells, by some rule of correspondence, and where the receiving industries may be thought of as benefiting from the R&D performed in the delivering industry in proportion to the share of the total sales of the delivering industry which each receiving industry buys.[13] These indirect R&D expenditures must then be thought of as incorporated in the products of the receiving industry in addition to the R&D directly performed in this industry. There is here a question here of which weights to use. One solution is to use the weights from an ordinary input-output matrix of product flows among industries. Alternatively, one may use other weights, where for instance data from patent statistics are taken into account.

These kinds of computations may be an interesting complement both to ordinary R&D statistics and to the question on investments in equipment and machinery related to innovations from the CIS surveys.

[13] See F.M. Scherer, 'Inter-industry Technology Flows in the United States,' *Research Policy*, Volume 11, August 1982, pp. 227-245.

IV. Understanding Innovation Indicators based on Patents

Eric J. Iversen

1. INTRODUCTION

"In spite of all the difficulties, patents statistics remain a unique resource for the analysis of the process of technical change. Nothing else even comes close in the quantity of available data, accessibility, and potential industrial, organizational, and technological detail."
(Griliches, 1990)

Patent-statistics form a tried if not entirely true indicator of technical innovation. To gain an idea of the continued usefulness of an innovation indicator with a tradition as long as that of patent-statistics, it is necessary to review features of it and its varied tradition. This chapter presents a critical discussion of the basis and background of patent-statistics as indicator and reviews its past and current applications.

A patent of invention is in effect a public contract that grants certain rights to the applicant for the use of a technical invention. As a contract, the patent engages the inventor (or controller of the invention) into a binding relationship with the state. In general, the inventor contracts to reveal detailed information about the invention in return for limited protection against others using that invention for the time and geographical area for which the contract is in force. In terms of the concessions made by the parties, there is a trade-off between the disclosure of detailed information by the inventor against the insurance of limited monopoly by the state. In this sense, the patent-system is designed as an incentive-mechanism for the creation of new economically valuable knowledge and as a knowledge-dissemination mechanism to spread this information.

Thus the patent-system has several apparent strengths in providing an analytical basis for technical change. In general the patent-system gathers detailed information about new technologies into a protracted public record of inventive activity, which is more or less continuous. Several of its more striking advantages as an innovation-indicator are;

1. Patents are granted for inventive technologies with commercial promise (i.e. innovation);
2. The patent-system systematically records important information about these inventions
3. The patent system collates these technologies according to a detailed and slow-to-change-classification system
4. The patent-system systematically relates the invention to relevant technologies
5. The patent-system is an old institution, providing a long history

6. The data is freely available.

The chapter begins with an introduction to key conceptual aspects associated with patenting as an indicator. Here, we will seek to establish what it is about the patent that makes it such a unique and promising observable of technical change. However, there are notorious difficulties connected to patent-statistics as indicator: these also need to be addressed. In the subsequent sections therefore we survey the qualifications that strongly condition the useful application of patent-statistics. What remains is to assess how patents have been used as an indicator, not only of technology output, but also of the flows of inputs and intermediary innovative components in the course of technical change. We will especially examine the use of citations and other information sources in the patent as indicators of important systemic interrelationships in innovation systems.

1.1. An early standard

The patent-system was of course not originally intended to provide science & technology indicators. We will see that this situation holds positive as well as negative consequences for its use. One positive aspect is that its detailed information predates the conscious collection of such indicators by a matter of centuries. At the same time, its first uses in this capacity were early. The application of aggregated patent-statistics can be traced back at least to the early part of this century.[1] Over the decades extensive experience has been amassed in applying patent-statistics to the study of the relationships between patenting activity and inventive activity, and, thence, invention and economic growth.

In more formal terms, this experience dates back to the work of Jacob Schmookler in the 50's and 60's, which set a standard in the systematic and critical use of patent-statistics. One of its many important aspects involved testing the relevant relationships. In the course of Schmookler's work, 'the dream of getting hold of an output indicator of inventive activity' became confronted with the reality of what patent-statistics could measure. His early work, which attempted to link a pioneering use of 'total factor productivity growth' to patent activity, was in this way forced to cede to a less ambitious but more realistic connection. The link was between aggregated patent-data and, "work specifically directed towards the

[1] For example, A study of the variations of inventive activity for different industries in Sweden, Germany, France, England, Austria-Hungary". Sweden, 1910. Cited in Basberg 1984.

formulation of the essential properties of a novel product or process."[2] Schmookler used this conception of *inventive activity* to analyze technology-push versus demand-pull effects in industries where potential uses for the inventions could be identified.

This work with patents has had profound consequences in demonstrating that technology is in fact – and should be in theory – an endogenous factor. Essentially, Schmookler rejected the view that industrial growth could be explained in terms of independent processes of technological advance. At that time it was widely believed that invention was an exogenous process, driven by scientific discovery. This view, in the form of the 'linear model' of innovation, failed to explain why inventive technological change occurred, and failed to account also for the critical fact that in many of the industries of the industrial revolution, output growth began before the new technologies were either invented or diffused.

Schmookler carried out a long-run empirical analysis of these ideas by looking at the links between invention and economic change in two industries which played a major role in American economic growth between the 1860s and the mid-twentieth century: the railways, and petroleum.[3] As a measure of inventive activity, he used patents granted by the US Patent Office in the relevant technologies. His economic indicators were a mixture of physical indicators (numbers of railroad rails, numbers of railroad cars, miles of track) and economic data (gross investment, stock market values etc). The first question was, did invention lead to economic growth; in other words, were increases in patents in an industry followed, with some kind of time-lag, by increases in investment or output? Schmookler showed that this did not happen. In some cases, the production indicators moved in advance of the patent series; in others, the two moved so closely together that it could not be claimed that either was leading.

This relationship was not confined to one particular technical field: it occurred in a range of areas within the overall railway industry; so an important element of the inventive process was a simultaneous increase in inventive activity within a range of fields relevant to railways technology. In petroleum, the general relationship between economic factors and inventive activity seemed to be one of simultaneous change. How should these trends be interpreted, and what are their implications for understanding inventive activity? Schmookler rejected the

[2] Schmookler, 1966. Cited in Griliches, 1990.
[3] J. Schmookler, "Economic sources of inventive activity", in N. Rosenberg (ed) *The Economics of Technological Change* (London, 1971), pp.117-136

idea that inventions cause output change on three grounds: firstly, it neglected the fact of parallel inventive behaviour within industries; secondly, the lead-lag relations were often the wrong way around, and finally it neglected the other complex socio-economic factors which cause output fluctuation. At the same time, it seems difficult to argue that there is any direct link between output variation and invention. Schmookler argues instead that output variation and innovative activity "both are the effects of the same or of correlated causes". The basic idea is that decisions to engage in research and in the development of new products rely on technological opportunity as a necessary condition, but given the existence of opportunity they depend ultimately on the availability of finance and on perceived potential profits. Schmookler used patent data, therefore, to argue that invention is not a process external to economic forces. Rather, it is a structured process: it depends of course on scientific and technical opportunity and feasibility, but within these constraints it responds to economic signals, particularly in the form of growing investment and final demand.

Since Schmookler, a vast array of other methods have been forwarded and tested using patent data. Taken together, this broad corpus has explored patent-statistics at the level of the invention and innovation, at the level of the firm and the business unit, at the level of type of technology and industrial sector, at the level of the region and the nation. The object of analysis has likewise varied. Various combinations of this data have been employed to answer questions about the nature of:

1. firms with technical activity
2. firms with technical markets in different countries
3. technical fields: invention and use
4. technology and science
5. technology and R&D
6. technology and economic activity

The breadth and depth of this work has generated many interesting though not entirely unambiguous results. The really ‘big questions’ involving the relationship between patenting and R&D and between patenting and economic development have been the least able to produce robust answers, especially when looked at in the framework of neo-classical economics. What has been amassed is experience of how patent-statistics can and cannot be used, especially in combination with indicators such as R&D expenditure. Some of these approaches will be surveyed in section 4.

1.2. In search of a new standard

One realization which has grown over time— even among some of the pioneers of the mainly statistical approaches that followed on from Schmookler's work— has been how important it is to integrate qualitative methods with quantitative ones[4]. This is due to the inconvenient fact that what patent-data tells us is strongly flavored by the context in which the individual patents were applied for and granted.

In this sense, historical analysis of patent records forms an important avenue for study. One interesting vein in this tradition is the work of MacLeod, who studied the reliability of patents in mapping the Industrial Revolution[5]. She used the evolution and the workings of the patent system in Britain to explore the relationship between patents and invention in a period when patent-statistics alone can be "misleading at best." MacLeod offers a complementary interpretation to Schmookler on what patents tell us. Where he showed the importance of demand-effects in promoting inventive activity, MacLeod—working with a different period and a different patent-system—suggests that patents provide a better indication of the development of capitalism in general than a record of the inventive activity for this earlier period. She showed a dramatic upsurge of patenting in the late 18th century, as industrialization began.

Today, the use of patenting as indicator is enjoying something of a renaissance. One reason for this is the increasing ease in accessing patent-data, which is reducing the difficulties of the previously cumbersome activities of compiling patent-data. Increased ease of access combined with quantum improvements in data techniques have opened for the investigation of other aspects of patent-data. Moreover, recent developments in innovation theory have stimulated new approaches to the interpretation of patent-statistics as an innovation indicator. In addition to the integration of historical analysis, approaches spawned by innovation systems theory, for example in the framework of 'knowledge systems' (Foray and David, 1995) have opened up new possibilities.

With the new situation of cheap and available patent-data, combined with new information sources, and a diversification of analytic approaches, the field has recently been taking stock

[4]See Scherer's recent work. Harhoff, Narin, Scherer & Vopel. Citation Frequency and the Value of Patented Innovation. (1997) , in which interviews supplement statistical filtering.
[5] MacLeod, Christine. Inventing the Industrial Revolution: The English Patent System, 1660-1800

of itself. The OECD has recently tried to codify the limitations and useful applications of patent-statistics as a science & technology indicator into a Patent Manual (1994)[6]. Other aspects of patent-statistics have likewise been collected: among others, Griliches, on econometric dimensions esp. in the neo-classical applications, Basberg, in more comprehensive terms (1984), Pavitt (1988) on its use in combination with other variables.

2. CONCEPTUAL DIMENSIONS

Three key dimensions of patenting activity—volume, orientation and change over time—provide the groundwork for measuring certain aspects of technologically oriented inventive activity. There are two main dimensions to the patent document and the system that administers it that are essential to shaping its application as a technology indicator on the conceptual plane. In this section we will first show how the *contents* of a patent, i.e. the establishment of patentability, make the patent a theoretically interesting proxy for innovation. Secondly we will show how the *form* of the patent and its long history make it a practical one. In the next section we will see how the aims and realties of the patent-system cause limitations and difficulties in using patents as indicators.

2.1. Background. Aims of the patent-regime

The patent-system involves something of a give-and-take relationship in which the state and the controller of the invention are brought together around the patent as a contract. The motives behind why the parties enter into a contractual arrangement necessarily influence how patent data can be applied as an indicator of inventive activity.

As a contract, the patent-system caters to the assignee(s)' basic desire to appropriate profits accruing to the invention while catering to the system's basic desire to have the details of the invention spread to others so that the system can build on new knowledge[7]. In this view the motives of the state involve (i) creating an incentive for actors in the economy to undertake inventive activities and (ii) to disseminate detailed information about inventive activities such that future generations can build upon them[8]. The motive usually ascribed to the patent-

[6] OECD. The Measurement of Scientific and Technological activities: Using Patent Data as Science and Technology Indicators: Patent Manual. Paris: 1994.

[7] For a seminal discussion of patents as a approrpiation/distribution regime see Arrow (1962). Note that a basic premise of the incentive aspect is based on assuring the inventor a chance to recoup the cost of his R&D investment.

[8] Scotchmer. On the Shoulders of Giants. 1991

applicant is on the other hand to use the protection from competition to appropriate the profits he manages to get out of the invention. Historically, one has interpreted 'profits' rather tightly to mean financial gains connected to the patented invention, either through developing it and commercializing oneself, or selling the rights to others who do. The justification for using patent-activity as a proxy for innovative activity stems from the two traditional roles of the patent-system: appropriability and information dissemination.

2.2. Patents and the identification of new and useful inventions

The first relevant aspect involves what a patent describes. The question is: what is it about patentability that makes patent-statistics an interesting innovation indicator? The short answer is that the examination patent-system's criteria for patentability. Even to the casual observer, the identification of a patent with inventiveness is intuitive. However, to appreciate the use of patent-statistics it is important to understand this relationship more closely. Specifically, three main criteria of patentability for which the patent-system tests should be emphasized here[9]. In order to be deemed patentable, a submitted technology must demonstrate:

1. Inventiveness: a certain degree of inventive activity[10] is generally required to qualify the device, contrivance or composition for patent protection[11] as an invention. The qualification of an "invention" serves to exclude "discoveries", e.g. of scientific principals[12], meaning prima facie that patent statistics are not a candidate for a 'science' but a technology indicator;
2. Novelty; a substantial claim to being new[13] with reference to existing art is required;
3. Utility; a potential useful application is expected for the invention. Note that also this requirement is not easily defined as what may be useful cannot be anticipated;

Box 4. 1. Patent as the unit of analysis: what does it reflect?

A patent;

- indicates that the technology in question is novel in relation to the existing art
- indicates a degree of inventiveness ('inventive-step' (Europe) or 'non-obviousness' (USA)),
- signals that the technology has industrial potential.

[9] We will talk mostly about one variety of a patent system, the examination system current in the Britain and the US. It is somewhat different from the registration-system (cf. France)
[10] Though not necessarily formal R&D, cf. Sirilli, 1986.
[11] It cannot be 'obvious to one skilled in the art' (in the US); alternatively, it must show an 'inventive step' (UK).
[12] Such 'discoveries' are expected to be published in scientific journals. Note however that the distinction between 'discovery' and 'invention' is not necessarily clear cut and apparently becoming less so. Cf. plant patents and other biotechnologies.
[13] Previous patents, journal articles or known uses.

Other characteristics:

- gives the rights-holder a monopoly to exercise the invention, which is limited in time (generally 20 years) and in geography (nationally, regionally according to convention)
- Key-aspects of the invention are published, including (in the USA) how best to exercise the invention.
- A protracted processing time (at least 18 months)

2.3. The form of a patent: the codification of innovation

In terms of its use as indicator, the second relevant aspect of patenting is the form of patent. In line with the patent-system's role as a knowledge distribution-mechanism, both patent applications (cf. temporary exception of the US) and patent grants are published. Patents are explicitly designed to lay open the main elements of technical invention. In fact, the original name of this institution belies this function. The term stems from *litteræ patentes*, entailing the sense of documents being laid open for inspection, where the documents describe technical invention. In this sense, the body of patents stands as a public record for inventive activity.

2.3.1.The Life of a Patent

This record is a living one and may capture the same technology at several points in time and space. Patent documentation can trace the technology from its initial application, through extensions into other geographical patent-regimes, to grant, renewal, until the term of patent-protection runs out (20 years). At the aggregate level, this documentation describes a selection process in which the number of patents becomes progressively smaller as many patents that are applied for are not granted, while of those that are never live to enjoy the full term of protection that the law allows.[14]

There are two critical points in this process that are reflected in separate patent documents. The first is the patent-application. Though not as yet examined for patentability, the application does serve as an early indication of the applicant's appraisal of the invention and its market-potential. The second type of documentation is the patent-grant. If the patent goes on to issue as a grant and the applicant pays fees for coverage in a set of designed states

[14] We are using the case of an examination patent-system requiring the payment of fees to insure renewal throughout the total allowable life of a patent. Such a system can with reservation be said to form the 'standard' regime. Details of how a patent-application matures in the context of various regimes can be found among other places in the OECD Patent Manual.

patentability and the applicant's subsequent evaluation of the market are indicated. A further indication of the value of the patent for the applicant is provided by his decision where relevant to pay renewal fees, which are generally set on a progressive scale becoming more expensive over time (after 3.5, 7, 9 etc years). Another indication of the patented technology's value for the applicant involves. The geographical coverage that is sought for a patent through extensions to other patent-regimes and the maintenance of already designated areas can be a strong indicator of the technology but also the cost-sensitivity of the applicant.

2.3. The anatomy of a patent

Before going on to review the practical considerations in using patent data, let us review the information sources found in a patent and some of the possibilities they hold. Below, the first page of a patent granted in the US has been downloaded from the USPTO online database[15] and laid out here for purposes of presentation. We have broken the first-page information into four separate sections: titular information, including the title and names of inventor and assignee; technological classification, in which the invention has been assigned classes within both an American and a standard international classification system; References cited, in which other patents (US and foreign) relevant for establishing prior art are listed by the examiner in addition to other references for example to scientific journals are included for the same purpose; and the Abstract which gives a brief description of the invention. In addition, first page indicates the number of claims for novelty the patent makes and the number of drawings that will be included in the detailed information that follows this cover page.

[15] http://www.uspto.org

Box 4.2. Example of the first-page information included in a patent

United States Patent number 5,768,508 Eikeland, June 16,1998

I. General Information

Title: Computer network system and method for efficient information transfer
Inventors: Eikeland; Martin (Bekkestua, NO). Appl. No.: 832,687
Assignee: Digilog AB (Oslo, NO). Filed: Apr. 11, 1997

II. Technological Classification

Intl Class (IPC) : G06F 15/16
Current U.S. Cl.: 395/200.32; 395/200.47; 395/200.54; 395/200.63
Field of Search: 395/200.47, 200.48, 200.49, 200.53, 200.54, 200.55, 200.61, 200.62, 200.63, 200.64 , 200.65, 200.32; 370/230, 232, 233, 234, 235; 707/10

III: References Cited

3.1. U.S. Patent Documents

Pat. Nr	date	name	class
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5,193,151	Mar., 1993	Jain	395/200.67
5,263,157	Nov., 1993	Janis	395/200.59
5,329,619	Jul., 1994	Page et al.	395/200.33
5,347,632	Sept., 1994	Filepp et al.	395/200.32
5,404,505	Apr., 1995	Levinson	395/610
5,500,890	Mar., 1996	Rogge et al.	379/91.02
5,504,744	Apr., 1996	Adams et al.	370/232
5,519,689	May, 1996	Kim	370/232
5,528,501	Jun., 1996	Hanson	364/443
5,572,643	Nov., 1996	Judson	395/200.48
5,610,910	Mar., 1997	Focsaneanu et al.	370/351
5,617,565	Apr., 1997	Augenbraum et al.	395/604
5,694,594	Dec., 1997	Chang	395/606
5,710,884	Jan., 1998	Dedrick	395/200.47

3-2. Foreign Patent Documents

Patent nr.	Date	Issuing PTO
0 384 339 A2	Aug., 1990	EP
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0 632 672 A2	Jan., 1995	EP
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IV. Abstract

A computer network connects information providers and end-users of network services, facilitates direct information to users, and gathers user responses. The computer network is designed to use otherwise idle bandwidth of the network transmission medium to transfer targeted commercial and non-commercial information to users while minimizing the delay of normal network traffic. User reports containing demographics and user responses are generated ensuring user privacy. Information providers can access user reports without violating user anonymity.

30 Claims, 10 Drawing Figures

Source: USPTO online database

For the purposes of designing indicators, the patent can be broken down according to the information it provides about:

1. Who the inventor(s) and/or who the applicant(s)/assignee(s) are. On this basis the activity of individual inventors or firms can be mapped, as can the relationship between them.

2. Where the inventors and/or assignees are geographically located. In addition, information about where patent application has been applied for; (cf. Grants from the EPO)

3. When the related patent applications were applied for and, where relevant, when the patent concerned was issued, amended or renewed;

4. What is patented. The published patent includes two indications of the nature of the patent. The first type is the written description as found in the title and the abstract (< 200 words) of the first page of a patent. This written information is intended to provide a clear qualitative idea of the technology. The second indication is how the technology is categorized according to the multi-layered classification system(s). Note that the patent can be fall into several classes or subclasses (74/551.3 and 74.551.2), in which the first listed is the Primary class and the following subsequent classes in which the patent shows novelty. In addition, there are different standards for classification: the local (here the US) and the international standard, the IPC. Concordance between the two is not always reliable.

5. And finally list of citations to other documents, including other patents and scientific literature. These citations are intended to establish the originality of the invention, and serve to identify the area (s) of the technical art that the invention builds on and differentiates the said invention from such antecedents.

3. DIFFICULTIES IN PATENT-ANALYSIS: PRACTICAL CONSIDERATIONS

As surveyed above, the general properties of the patent strongly support the use of patent-data as an indicator of technical innovation. In this chapter, we survey the use of patent-data as a 'lens' through which to regard the development of technical inventions and emphasize some of the main aspects that influences what that lens reveals and how it does so. We will see that this is a lens that magnifies some types of activities and minimizes others; ignores some and generally lumps together the development of technologies that have vast economic impacts (e.g. ulcer medicines) with those that have none.

3.0. Factors that shape what the patent-lens reveals

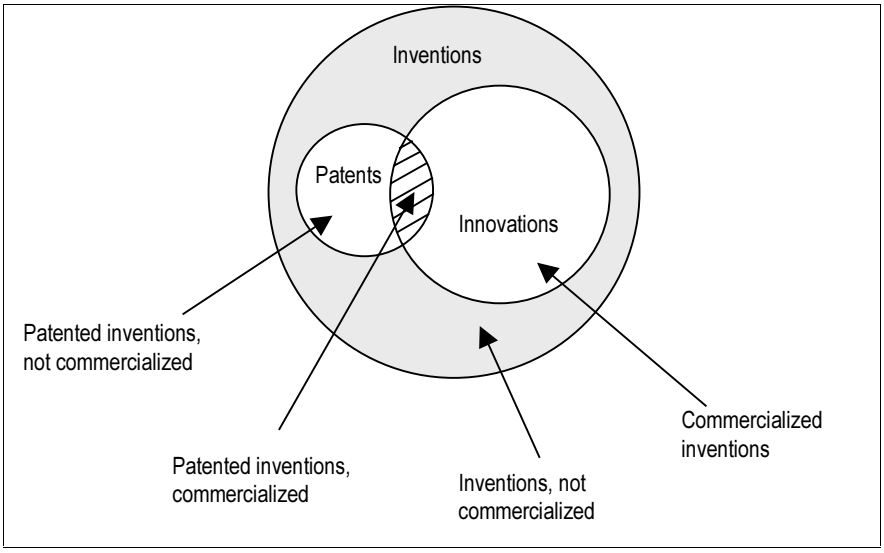
A prime assumption behind the use of patent-data as an indicator is that all inventions are equally patentable, that all inventions have the same propensity to patent, and that, in some way, the patented inventions are of similar economic value. In practice, this assumption does not hold. Not all inventions fulfil the patentability criteria nor are all inventors equally disposed to apply for patents. In addition, the operational characteristics of the patent office involved will ultimate affect what the patent-data reflect. Furthermore, the value that patented technologies realize is bound to differ according to many different variables.

A conceptual picture of the relationship between invention, innovation and patenting serves to dispel the common notion that one patent represents one invention and that this equals one innovation. If we assume that, at any given time, there exists a universe of technological inventions which show some novelty in relation to existing technological art, it becomes clear

that only some of these inventions will eventually show economic potential and still fewer will realize that potential. This is to say that a subset of the total volume of inventions realize the status of innovations. The question is then how well patent-statistics correspond to the total volume of inventions and moreover to those that become innovations.

A hypothetical universe of technical inventions is suggested by Basberg (1984) and presented below. The figure indicates that, of the total universe, only some inventions are patented and only some actually realize any economic impact (i.e. become innovations). In terms of patenting as an innovation indicator, what is interesting is where these two subsets overlap to cover 'patented inventions that are commercialized'.

Figure 4.1: Invention, Innovation and Patenting. What is the relationship?



Source: Basberg, 1984.

As the figure indicates, the initial problem that faces the interpreter of patent-data is that the overlap between *innovations* and *patents* forms far from a perfect union. Instead, a substantial set of 'innovations' are not covered by patenting while patenting covers a substantial set of inventions that never realize any direct economic impact. Based on this initial observation, the assumptions noted above need to be strongly conditioned before patent-data can be reliably employed as an indicator. There are four main factors to consider that shape the significance of the data:

1. What is effectively patentable;
2. What actually motivates the patent-application;

3. How patent-offices (PTOs) process applications;
4. And, least predictably, what value the patented technology has on the market.

3.1 What is effectively patentable?

Would inventions be made if there were no patent-system? In practice the answer is at least "it depends". However, an orthodox reading of the theory of the patent as an incentive mechanism would tend to assume that the answer is "no"[16]. Such a strict interpretation then implies that all useful inventions are patentable and therefore observable in the patent-statistics. The first way in which this argument is faulty is that not all useful-inventions qualify for patenting.

There are several inherent qualities of the patent-lens that shape what is revealed through it. We will see that the ideal situation in which one patent represents an innovation, and where all innovations are represented is made impossible by the lens. The following qualifications need to be made:

- the 'utility' requirements does not necessarily filter out inventions without economic potential.
- Although the patent system is designed to allow inventive activity that shows commercial promise, there is no real standard for the *utility* of the inventions that the individual patents describe. The patent-system has no way to forecast the real potential utility and therefore the standard for this aspect of patentability is fairly loosely interpreted. As a result, the utility criterion is not as rigorously exercised as might be imagined and we can therefore not expect a priori the exclusion of inventions with no economic future, neither in theory nor in practice[17].
- Patent data tends to focus on innovative activity of a technical rather than scientific nature, though the distinction is by no means clear in practice.

In general, the rationale is that, "(p)atents are the outcome of the part of scientific and technological activities which have a proprietary nature and are likely to generate business applications, in other words they are more likely to reflect technological rather than scientific

[16] That is, under perfect information, and non-excludability imitation is virtually cost-free. The would-be inventor has therefore no incentive to invest in an invention.
[17] Machlup indicates that the utility criterion is mostly exercised to hinder patenting potentially dangerous or destructive technologies.

activities." (Archibugi, 1992. p 357) However, even this criterion does not help us get a firm grasp on what the patent lens includes or excludes. Indeed the distinction between science and technology is not entirely clear when it comes to patenting. In part the obscurity reflects inherent difficulties in distinguishing science from technology; but not least does it reflect the nature of looking through the patent-lens. One aspect involves the degree to which emerging technologies that are increasingly science-based, especially certain bio-technologies, are eligible for patenting. (Modified) organic matter can certainly show commercial potential but whether in certain cases it can show an inventive-step is far less clear. For example, there is currently a debate over whether genetic material used as 'tags' can qualify for patenting. This sort of case tests the interpretation of the individual patent-office, whose practices differ considerably on this question (cf. EPO vs. USPTO, see below). More generally, they indicate that the orientation of patent-activity is moving farther right along the continuum of invention to include "discoveries".

➨ Patenting favors certain types of technical innovation, and tends to downplay the significance of, for example, process-oriented innovations.

One property of the system is that many "innovations" simply do not qualify for patentability. Examples abound (although software is no longer relevant). Taylor and Silberston[18] note for example that a major source of innovation of the textile industry involving yarn-texturization revolves around the vast improvement in the speed and reliability of the machine processes. Much of this type of innovation, despite its novelty and utility, is just not patentable. This indicates what is excluded by the patent-lens. The patent-data therefore incorporates systematic biases that become amplified by what motivates the patent applications. (cf. below)

➨ What is patentable can change over time, introducing discontinuities that need to be understood.

One element that the Basberg figure above did not illustrate is how the relationship changes over time. We noted above that one of the advantages of the patent-system is that it is conservative where regards changing its classification system, by which it collates patents. However, new technologies emerge and old ones die out, meaning there are discontinuities in the data-set. One should be wary of these. A case in point of how what is considered patentable invites a spurious relation is in the opening of software-patents in the US. In the

[18] Taylor, C.T. and Z,A. Silberston. The Economic Impact of the Patent System. 1973.

mid-eighties there were no software patents issued in the US, but by 1990 1,300 had been granted. By the end of 1997, the PTO expects 37,000 such patents to issue. It would be wrong to assume that this incredible growth in patents reflects a proportionate increase in the progress of software technologies for the period. It reflects a backlog of patents and signals that patent-examination in this field is as of yet immature.[19] Further, compare these numbers with 'European patents' and one could wind up concluding that Europeans are terrible at software technologies, as they hold relatively few software patents. However, one central reason why Europeans have not patented more extensively in software is that European Intellectual Property Rights regimes are somewhat stricter about granting software-patents, meaning more software is protected under copyright.

Another general aspect involving the relationship over time is that maturation from invention to innovation is, where present, not instantaneous but can vary from a short period of time to a long gestation period. This means that even where the patent lens indicates that the we are observing innovations, we will be looking at innovations in the past, present and future.

➨ Certain inventions can be accompanied by many patents during the course of the technology's life while others will only be indicated by a single patent.

The other side of the question involves what is included. One dimension of this is whether the patent describes a basic-invention or an improvement. Indications are that, "Patent activity may extend over the whole of the product life-cycle: From protecting the basic invention, through those patents related to product and process engineering, to a myriad of improvements and blocking patents."[20] In general, there is no real standard for the scope of a patent. It has been reported that the launch of a new IT product was followed by the application for 100 patents. (Aharonian's Patnews list).

3.2. WHAT ACTUALLY MOTIVATES THE PATENT APPLICATION?

In general one assumes that, in theory, the inventor faces a decision either to patent or to rely on alternative ways of appropriating the profits from his invention. The choice is commonly conceptualized in dualistic terms as either involving patenting or keeping the invention secret while attempting to commercialize it and thus collect returns on the R&D investment. In practice, the choice facing the inventor is more complex than a simple either/or decision. The

[19] Cf. Greg Aharonian's observations in Patent-news: patent-news@world. std.com
[20] K. Pavitt. Technical Innovation and British Econommic Performance. London 1980. P. 42 (in Basberg, 84)

inventor's propensity to patent can have either an inflationary or a deflationary effect on the volume of patenting and, in any case, a skewing effect on its technical orientation.

3.2.1. Appropriation

The decision to patent generally involves some sort of choice in which uncertainty plays a role. The rational choice facing the inventor is whether patenting protection is the cheapest and most appropriate form by which to collect returns on his invention. In this situation the inventor may attempt to develop the invention while keeping its essential properties secret; rely on first-mover or other advantages, or utilize other, more applicable rights. The one objective criterion the inventor has in this decision is the knowledge of the base costs of patenting vs. other protective rights, such as trademark protection: there are substantial costs involved in drafting, applying for, maintaining and litigating patent protection. Knowing this, the rational inventor must expect that the potential profitability of a technology is greater than these costs of patent-protection and that the alternative avenues for appropriating returns are more expensive.

In reality circumstances that affect such a choice will be very much grounded in the inventor's individual situation. One central idea of using patent-statistics as an indicator is appreciating that indeed these circumstances affecting the propensity to patent depend on the type and the market-structure of the technology. Appropriation conditions vary for different technologies. The decisive factor is the relevant market-structure.

- Technologies with high R&D costs, and low imitation costs such as pharmaceuticals will have a strong propensity to patent.
- Technologies that have short product horizons will have less of an incentive to patent for appropriation-reasons because the processing time of patents can be several years[21]
- Technologies which are easy to keep secret (cf. the process involved in making Coca-Cola) will tend to prefer secrecy;
- Technologies, like alimentary innovations, which lend themselves to other IPRs like Trademarks (Coca-Cola) will prefer such coverage (because it is less costly to process the application, and coverage is indefinitely renewable)

[21] Though they may have other motives to patent, for example to safely enter cooperations. See below.

Further, the choice will be affected by characteristics of the firm. The central aspect is that different classes of firms will react differently to the costs of patenting. Small firms with little in-house expertise about IPRs will have a different propensity to patent from a MNC with as many IPR lawyers as researchers (not unheard of, especially in the ICT world) and pay-schemes geared to number of patents applied for.

3.2.2. Indeliberate factors

There are also other criteria that will affect the choice of whether or not to patent than cold calculation. In the case of a substantially new technology, the inventor might, for lack of precedence, be unsure of the patentability of the invention. There has for example been considerable confusion about if and in what situations software can be patented. Faced by uncertainty about the patentability of an invention, many will choose other strategies by which to profit from the technology in question. A more common version of this problem is a general uncertainty of what patenting involves. Another type of uncertainty involves a sort of cultural disposition against patenting in general. This disposition can infect the level of the firm, groups of firms (especially small or academically oriented firms), or of the country relative to other countries.

3.2.3. Strategic motivations

There is also the opposite case, that of an aggressively pro-patent cultures associated with large firms having Intellectual Property Rights departments. One element of this propensity to apply aggressively for patents is the desire to shelter against piracy of one's invention while one attempts to develop it to market. However, there are other motives involved which will affect the number of patents applied for (and, issued given the fairly low standards for qualifying for patentability, see below). One of the more important involves using one's patent portfolio in relations with other companies, especially in licensing relationships or in R&D collaborations. In addition portfolios play important roles in mergers and acquisitions. Both in competitive and collaborative ventures, patents are important bargaining chips. In addition, there are several types of ulterior motives to patent applications that do not necessarily involve a positive attempt to develop one's own technology nor to develop the basis on which to collaborate with potential partners. Patenting might have a primarily internal function of grading employees. Patenting might be used to block the innovative activity of one's competitors. There exist firms who patent not to develop their own ideas, but to ensnare less wary competitors in order to extract royalty payments usually by threats of

litigation. Such strategic uses as blocking-patents or patent mining do not directly contribute to a better picture of technological change.

3.3. How do patent offices process applications?

Despite recent efforts (in the EPO, and between the US, Japan and Europe) to arrive at a certain standard for what can be patented and how, there is a significant difference between the form and contents of patent-statistics from countries as close as France and Britain. Such differences will condition the single-country analysis of patent-statistics and significantly affect cross-country comparisons.

There are two main types of patent-systems. Of these, the *registration patent-system* (e.g. France), is the less interesting as a stringent proxy for innovation. In it, patent applications are largely registered without being tested for patentability[22]. The testing process is largely carried out in the courts, where claims can be contested by other economic actors and either be removed or stay standing. The advantage is that the lag between application and grant is much shorter than in the otherwise, more interesting *examination patent-system* (e.g. USA). Our description above, in which patentability requirements undergo a long examination process, is based on this sort of system. However, there is also quite a bit of difference within these systems, in terms of patentability and practice.

First there are different types of patents. For example, the US Patent and Trademark Organization (USPTO) issues utility patents, design patents and plant patents: the first for technologies demonstrated functional operational novelty and utility, the second for artifacts whose novelty is primarily ornamental and the third for non-obvious uses based on organic substance, such as a plant. In addition, special sui generis rights such as mask works for semiconductors. Of these, the utility patents form the basis for what are thought of as *patents of invention.* Not all patent offices grant for this range of protection. One should be wary of such differences in the qualification and the classification of technologies. A current international rift involves the patentability of biotechnology developments such as plant patents. It should be said, that where regards classification, most countries list an international standard of classification (IPC) in their patents.

[22] This seems to be integrated into the USPTO in the form of Inventive Disclosure Documents or Provisional Patent Applications.(from 1995)

A further example of differences in patentability is that some systems (e.g.. the German) allow protection for 'petty patents', which generally reflect incremental improvements in technology. Such rights are generally supplementary to the main patents, as is the case of Gebrauchsmuster (utility models): these rights have shorter life-spans than the standard utility patent.

The period of protection is another procedural dimension that varies according to the granting office, though this is being brought into line by international convention. The common period is 20 years after filing, although if we are looking at patents granted in the US before June 8, 1995, the applicable time-span was 17 years from grant.[23] Some South American countries on the other hand have used a system based on 5-,10- and 15-year protection periods that depend on the type of invention. Such practices indicate the potential for vastly dissimilar regimes. Further, some patent systems require a renewal fee in order to keep the patents active through the whole time-span (renewals).

In addition to such differences between systems, there are also longitudinal variations within a system. One type of change was noted in the change of the period of protection in the US. Another type is the change in the effectiveness in patent examination. Jumps in the rates of patent granted by a certain system might be a better indicator of "bureaucratic mirage", telling more about how many examiners are employed at the PTO at any given time and less of the nature of technological change.

3.4. Variable economic impact of patented innovation

In general, structural, institutional and discretionary factors affect the quality of patent-data, influencing what is picked up and what is left out by the patent-lens. Some of the specific factors we have seen include:

- Cross-country comparisons reflect differences in institutional practice;
- Cross-industry comparisons will reflect the fact that the value of patenting will vary across different technologies, owing to different market-structures and different patenting cultures. Patenting for products is for example more likely than patenting for processes;

[23] Apparently, there are exceptions to the period of protection, for ex. for certain pharmaceuticals.

- Cross-company comparison will reflect variations in firm-level patent-strategy, especially differences between large and small firms;
- Use of patent-statistics in time-series is problematical: patent-classifications, while fairly stable, change over time making especially long time-series comparisons susceptible to discontinuities. One aspect of this is that patentability criteria change over time (cf. software in the US).

Some of these distorting elements, when taken into account can be adjusted for or at least allowed for. When allowances are made that not all inventive activity is reflected in the patent-statistics, however, it becomes important that what is represented is at least of a representative quality. Despite this, raw patent-statistics do not indicate how many patented inventions have or will have any economic impact, let alone how much impact they will have.

The question of the relative value of patented technologies is an essential one, especially where the object of analysis is connected to questions of inventive performance or R&D performance. A direct indication of relative value which the patent-system does provide involves the paying of fees. Patenting can be resource intensive, both in the drafting, application, renewal and enforcement of one's rights. The fact that an application is sent indicates a certain expectation of returns (though these may not just be expectations of profits but negative effects on one's competitors); the fact that one renews one's patents (after 3.5, 7 etc years in the US) further indicates the importance of the invention. Analysis of renewals (cf. Shankerman and Pakes, Pakes and Simpson) is one way to approach the question of value. Another way that has been used is to connect patenting econometrically to other variables such as stock-market value. A third is through surveys. Aspects of these and other approaches are surveyed in the next section.

4. REVIEW OF GENERAL APPROACHES

Patent analysis varies considerably in terms of its aims and in terms of what patent information is selected and at what level of aggregation. Nonetheless, two main sets of approaches can be identified. The first involves using patent-statistics as a 'technology output' indicator while the second involves using other patent-data to map "spillovers" between different knowledge-bases. Both approaches proxy different dimensions of patenting activity and make fundamental assumptions about the link between patenting activity and innovative activity and in some cases economic performance as well.

4.1. Technology output: Proxy of inventive activity, sector specialization and economic growth

Patent-statistics are most traditionally utilized to proxy the results of technically oriented inventive activity. The fundamental hypothesis is that a patent represents a codification of inventive, technical activity occurring along the "technological frontier." This hypothesis is made on the basis of the *novelty*, *utility* and *inventiveness* criteria of the patent reviewed above. In such analysis, a line is drawn (more or less directly) between the inventive activity of the patent-applicant and his patenting activity.

Patent-statistics are generally used in three ways as a proxy for inventive activity. The main approach simply involves patent-counts. In patent count analysis, the volume and technical orientation of a population's (firm, industry, country) patenting activity is used to study everything from its patenting practice over time to the direction and depth of its R&D activities. It has also been common that these counts are then pegged to other indicators of the population's production factors (R&D, workers, turnover). This second general set of analysis of patent-intensity is used to arrive at performance indicators. The third application in turn involves comparing the patenting activities of different populations. Patent share analysis essentially compares the orientation, volume and development over time of the patenting activities of different populations.

4.1.1.Patent counts

Patent counts generally focus on the information sources in the patent involving the who (inventor, assignee), the where (their addresses) and the what (the classification of the invention. Such counts make up the basic data-set for most patent-analysis and is used widely notably at the national level by the OECD in their MSTI (Main Science and Technology Indicators) series. The pure enumeration of patent applications and patent grants and arrangement by technical categorization—though of limited analytical value in itself—has many applications. They are instrumental in identifying systematic changes in patenting habits, for example the marked increase of Finnish patenting activity in the telecommunications field, the marked increase in Japanese patenting at the global level, or the tendency towards increased foreign patenting in general.

More specifically, the patenting behavior of individual firms can be monitored using this simple method. Patent-counts have with the increasing availability and sophistication of

electronic patent-databases become a common tool in the business world to stay on top of competitive trends in one's field. In increasingly international markets patenting has become a good indication of company strategies, potential collaborators or potential rivals. It supplies a useful indication of the diversity of company competencies and inventive activities, on which the circumspection concerning patent-specificity is imperative. As with patenting more generally the activities of pharmaceutical companies are among the most visible actors.

Raw patent-counts reflect of course any inherent weaknesses in the patent lens and therefore give an imperfect measure of innovative output. Techniques are used in attempts to correct for the distortion, for example in weeding out minor inventions that never become innovations: in other words they try to bring into focus the overlapping area in our figure above where patents and innovation meet. Techniques involve inserting filters to screen the data, often by focusing on patents for which renewal fees are paid. The real lifetime (how long it is renewed, within the 20 years) of a patent in relation to the average for the population can be a strong indicator of the viability of the innovation and the value of the patent. A recent study, building especially on of the authors' pioneering works with renewal-data, claims to reduce the noise in patent-counts by 50% using a simple weighting-scheme.[24]

Besides renewal, the extension of patent rights to other countries is used to indicate different aspects of the potential value of the technology involved and/or the strategic market interests of the assignee. Patents that are sought abroad, especially in multiple countries and especially where renewal fees are maintained are expected to indicate important technologies for the patentee. Grounds for circumspection include the need to make allowances for the characteristics of the different patent-offices involved, the need to make allowances for the propensity to patent certain technologies abroad more than others, or the need to make allowances for the potentially strong effect of macro-economic conditions on patenting activity. For these reasons the use of patenting in the US is advised and large time-series are recommended.

Many other applications are possible as long as the caveats of using patent-data are observed. One last application can be mentioned here to study patterns in the inventor/assignee

[24] Lanjouw, J., A. Pakes & J. Putnam. *How to count patents and value Intellectual Property: Uses of patent renewal and application data.* NBER paper series. 1996.

combinations in patents. Such patterns can be used to identify and study strategic collaborations. Regular combinations between firms registered as assignees witnesses to concerted efforts and complementary knowledge-bases.

As the literature emphasizes, patent-counts should be combined with other data-sources (cf. Pavitt, 1988) including more qualitative sources such as surveys and interviews in order to realize their potential as an indicator.

4.1.2.Patent-share

The second basic type of analysis of patenting on its own terms has involved comparing the volume and technical distribution and evolution of the patenting activities of different populations. The OECD for example has long compared the foreign and domestic patenting of different countries over time. Such cross-country comparisons have been used to indicate inter alia relative levels of 'technology dependence' or 'technology transfer.'

Many complications are introduced when patenting-activity are compared. The main set of problems involves structural, institutional and discretionary variations in the propensity to patent as surveyed above. The sector specialization of a country will for example influence the volume of patenting. So will firm-size. Variations in the institutional characteristics of the relevant patent-examiner will also affect comparisons in the domestic patenting of different populations while the individual population's international presence will to a certain degree condition foreign patenting patterns. Such considerations again raise critical questions concerning what assumptions are made about different populations and what data sources are used.

Most patent-share analysis utilizes a standard patenting-venue, such as the US system. The ongoing improvements in the quality of patent-statistics are also making world patenting-data more accessible. However, such data-sets as the recently available Triad data (US, EPO and Japan) have a certain large-firm bias. Patent-share analysis is based on comparing the relative ratios of the patenting activity of the populations involved. The activity of the actors is thus made relative the total universe of patenting to point out peculiarities of the individual population's patenting activity.

Pegging patent-activity to the total population acts to benchmark the performance of the population. This type of study reveals relative patterns of sector specialization of patenting. Certain approaches such as Revealed Technological (Comparative) Advantage (cf. Jacobsson and Philipson, 1996) are used to index the relative dimensions of one's patenting activity. In addition, such indexes can be normalized through statistical techniques to provide indicators at the level of single or multiple patent offices. These can be analyzed to indicate something about the population's patenting 'advantages': for a short survey of 'technometric'approaches, see box 4.2, based on Grupp, 1992.

Box 4.3: Specific indicators to analyze patent-share: "Technometrics"

I. Single PTO indicators

1. Revealed Technological Advantage (RTA). RTA is the basic Activity Index by which the ratio of a population's patenting in a certain technology to its total patenting activity in relation to the comparative ratio of the total patenting universe.

2. Revealed Patent Advantage (RPA= Patent Specialization Indicator) uses a statistical technique to correct for structural biases: 100 ln RTA (least squares distant measurements)

II. Multiple PTOs Indicators

1.Revealed Technological Production (RPT). RPT provides a bandwidth of technological positions.

2.Derivative= International Technology Production (ITP)
-non-biased patent output.. Geometric mean between PTOs involved

Source: Grupp, 1992

Patent shares can thus be interpreted to reveal relative 'strengths' or 'weaknesses' in relation to the whole population. Trends in how the relations change over time can for example be used to indicate how 'innovative' a population is relative to the changing 'technological frontier', measured by patenting. One indicator of the 'innovativeness' of population is the degree to which given populations are active in those technologies in which patenting is growing most over time or whether they are more concentrated in less 'innovative' areas. (c.f. Laursen et al., 1996)

4.1.3.Patent-intensity and comparisons

The main body of patent-analysis has involved pegging patent-statistics— both patent-counts and patent-share— to other indicators of the population's production factors (inhabitants, workers, R&D expenditures, turnover, trade). The study of patent-intensity is in its various forms used to arrive at performance indicators of different flavors. The combination of patent-data and other data-sources has been valuable inter alia to use correlation-techniques to test the analytical power of patent-statistics as an indicator. The results have not always been

convincingly robust, though many general as well as some specific lessons have been learnt thanks to this work.

One additional difficulty found in this work is that correlations with other variables entail close comparability. Because the patenting system uses a sui generis product based classification system (of which there are different types), it is inherently difficult to attach patent-statistics to statistics that are based on standard industry-classification standards. Several keys have been developed to correlate patent classes with industrial classes[25] (cf. Merit) but it is still not unproblematic to move between patent-classes and industry classes nor yet between different patent-classification systems.

A central area of this work has revolved around the relationship between patenting as an indicator of knowledge creation (or "accretion") and R&D activity. This line of inquiry has for example attempted to indicate scale advantages of R&D activity and has been at pains to correct for R&D productivity rates for small firms vs. large firms (cf. Simonides 1996) or for industry. The results of such econometric, typically neo-classical approaches have not been unambiguous, though lessons have been learnt. (cf. Griliches 1990)

Another central area of work has been in trying to model the value of individual patents, which again has been a central problem in using patent-statistics. Different approaches have been used to gauge value: as indicated, patents that renew (Pakes & Simpson, 1989), that extend protection internationally, and that are cited often (Trajtenberg, 1990) and by a range of different types of patents (Jaffe & Trajtenberg (1998) indicate patents of higher value. Harhoff, Narin, Scherer & Vopel, 1997) for example indicate in their multi-national study that for the most cited patents, each US citation implies an average of more than a million dollars of economic value.

In addition to analysis of patent-renewal or tracing patent-families, the patenting activity of large firms have been correlated to the market-value of the firm as measured by stockmarket-prices (Pakes, 1985) or equity plus debt. (Griliches, 1984) A more modern study of correlations investigates the importance of firm-level competencies. Here the object of study

[25] For example, Verspagen, Bart, Ton van Moergastel and Maureen Slabbers. MERIT concordance table: IPC - ISIC (rev.2). MERIT Report, 94-004. At http://meritbbs.unimaas.nl/rmpdf/rmlist94.html

is the relationship between the competencies of the firm as indicated by patent-data and its product-ranges. This type of study (cf. Patel & Pavitt, 1997) has at the aggregate level indicated patterns of diversity in what a corporation knows in terms of what product-markets it is involved in. More untraditional forms of analysis will improve as the data with which patent-statistics are correlated improve.

4.1.4. The particular applicability of surveys

In addition to these specific approaches, one meta-approach that has substantially aided patent-analysis and promises to future improve our understanding of what patent-statistics can tell us involves surveys. The use of surveys has been, is and promises to continue to be a useful complement to patent-analysis. Studies, notably the Yale-study, have provided interesting, but again not final results on such issues as the variable propensity to patent by firm-size, or type of technology. Our understanding of the rate of commercialization among patented technology has for example been improved, establishing the importance of patents for commercialized inventions and the variable propensity and value of patenting between products and processes.

In Europe there are specific questions linked to the move towards a standard patenting environment from a diverse institutional and cultural practices. The Pace-study provides provocative indication of the variable propensity to patent among large European firms in different European countries. This rich data-set has provided interesting indications of the patenting strategies of large European firms. (Arundel, A. and I. Kabla. Patenting Strategies of European Firms: An Analysis of Survey Data. 1996)

Useful information has also been collected by the European Patent Office itself, covering a huge set of firms. (cf. Van Leuwen, 1995) The EPO study, which has a pragmatic and partially commercial object, provides useful information about various relationships between firm-characteristics and patenting-behavior that are relevant activities of that patent office.

4.2. Mapping knowledge-links between different inventive inputs[26]

The second main type of patent-analysis involves the study of links between patented technology and other areas of innovation to which it can be related. This type of analysis

typically suggests an interdependence between the R&D carried out in one field of technology and activities in other fields. The interaction between fields— whether they be in the form of user-producer relationship involving the technology or the research co-operation of different areas— creates a uni- or multi-directional learning vector in which knowledge flows from the one area to the other. This knowledge may be embodied in a technology which is in some form bought[27]: alternately this knowledge may flow in a disembodied form (e.g., from the research infrastructure, via the range of researcher competencies).

Studies of such 'knowledge-spillovers' have been made more important by recent 'systems' approaches to innovation, e.g. 'knowledge systems approaches'[28]. Such approaches indicate the importance of the systemic properties involved in the creation of innovative ideas, the longer-term creation of knowledge and especially the interaction between different knowledge-bases. The flow between knowledge-bases within the economy acts as an inter-sector learning process. This process is important for the economy as it contributes to the 'virtual circle of the generation and distribution of economically valuable knowledge' (Foray, 1995).

Since it is a general policy objective to stimulate the creation of innovative knowledge and the potential synergetic interaction between potential areas of collaboration, a tool like patent data which gives such detailed information about inventive activity and indicates flows between knowledge-bases is clearly important. There are several approaches that use different information sources in the patent essentially to locate knowledge-spillovers. One approach casts patented technology as an input in some form to the technological activity of other actors such that the invention forms an 'embodied spillover' to the recipient industry. Ultra-light, ultra-strong materials may for example be created in the aerospace industry but may be used extensively in the production of bicycle frames: improvements in materials can therefore be said to spillover to touch off innovation in the field of sports-articles.

[26] This section builds on earlier work. Iversen, E. *Knowledge-bases and interactions in the Norwegian Knowledge System: a patent share and citation analysis.* Step-Report. Forthcoming.

[27] This entails the other sort of spillover in Grilliches' classification, a rent-spillover. Cf. Hauknes in the Mapping book.

[28] Foray, 1995.

Alternatively, the patent may be assumed to involve knowledge inputs. In the latter case the central hypothesis is that knowledge-'spillovers' between different innovative knowledge-bases can be traced via the citations a patent makes to other patents and those it makes to other publications, such as journals. (=Non-Patent Literature) The assumption here is that such citations indicate knowledge-bases that the patent builds upon. The rationale is that such citations are made (on the first page) by the patent examiners to establish in relation to the 'prior art' of which the patent claims to show novelty.

4.2.1.Technology-Technology Flows

Analysis that attempts to correlate the industrial heritage of a technology and its probable industrial usage has a long tradition. It aims to identify regular patterns by which technologies move as an embodied knowledge 'spillover' from one 'innovation producing sector ' and a 'innovation using sector'. A pioneering work using US data is the Yale-matrix, in which Scherer improves an approach already extant in Schmookler, using better data sources, to study the links between R&D and productivity growth. [29] The matrix suggests—with certain qualifications— that productivity benefits accrue to the R&D using industries less than to the R&D originating ones. This sort of approach however poses difficulties both in identifying technologies with industries and reliably connecting the innovation producer with its user.

A related approach investigates the relationship between technological activities by linking information in the individual patent. It was noted above that patents are often classified according to primary and secondary classifications that are relevant to their novelty-claims. In the computer-networking patent above, the invention was for example listed in only one primary classes (US class 395: "Information processing, system organization"), but four sub-sub classes (200.32, .47, .54, .63) which involve different aspects of information processing:

II. Technological Classification

Current U.S. Cl.: 395/200.32; 395/200.47; 395/200.54; 395/200.63

This indicates that the technology is firmly centered within the *Information Processing* class, but that its claims for novelty involve different aspects of this sort of technology. The claims in many patents however span different primary (ie the first class given) and secondary (the following classes) technology classes. One promising use of patent-data assumes that the

[29] Scherer, F.M. Inter-industry technology flows in the United States, Research Policy #11. (1982))

relationship between the primary and secondary classifications demonstrates disembodied knowledge spillovers between the different technological areas involved. In a highly relevant work, Schmoch, Muent & Grupp (1996) have suggested this approach to measure spillover-effects.[30] Verspagen et al. have explored this relationship notably using European patenting. In the latter case, an ambitious study[31] utilizes different types of secondary classes in the EPO system ("invention information" and "additional information") to identify knowledge spillovers from one area of R&D to others. This source of spillovers is then connected to larger productivity questions.

The third type of approach used to study knowledge spillovers between technological invention involves how patents cite previous patents. Here the principle is basically the same. The classes to which a set of patents belongs is compared to the classes of those patents it cites. The implication is that the technology area of the citing patent is in a sense a recipient of knowledge from the technological areas to which it cites. In the case of the computer networking patent example, the first-page (examiner) cited 15 US patents, with four different primary classes, and five non US patents:

III: References Cited

3.1. U.S. Patent Documents

Pat. Nr	date	name	class
4,991,172	Feb., 1991	Cidon et al.	370/400
5,193,151	Mar., 1993	Jain	395/200.67
5,263,157	Nov., 1993	Janis	395/200.59
5,329,619	Jul., 1994	Page et al.	395/200.33
5,347,632	Sept., 1994	Filepp et al.	395/200.32
…etc			

3-2. Foreign Patent Documents

Patent nr.	Date	Issuing PTO
0 384 339 A2	Aug., 1990	EP
0 570 683 A2	Nov., 1993	EP
0 582 537 A2	Feb., 1994	EP
0 632 672 A2	Jan., 1995	EP
WO 97/39548	Oct., 1997	WO

The citing patent can therefore be seen in a certain sense as receiving knowledge from areas in which these predecessors have patented. The networking patent cites a patent (Cidon et al) in a primary class 370, indicating some relationship between the 'information processing' technology of the patent (US class 395) and 'multiplex communications' technologies of the cited patent (US class 370). Further, patents in cited in class 379 "telephonic communications" and 364 "electrical computers and data processing systems". Aggregating

[30] Schmoch, Muent, Grupp. *New patent indicators for the Knowledge-based economy.OECD draft report. 1996*

[31] Verspagen B., B. Los. (1996) Identifying R&D-spillovers and estimating their economic impact. MERIT Report.

this type of link for whole populations of patents can therefore reveal more robust relationships between related areas of technologies as well as between the agents who patent.

There are several aspects to this relationship that can be studied. One is the technology-based linkages that can be reflected at aggregated levels. Other approaches involve focusing on citations linking the patenting agents (assignee and/or inventor). By using the address information in cross-referencing patents, studies of citations can be used to identify 'technological neighborhoods' in which inventive agents are geographically localized. (c.f. Jaffe, Henderson and Trajtenberg, 1993) This type of approach can turn up clustering effects which can be especially interesting in studies of national or regional innovation systems (NIS). Here it has been indicated that patents are significantly more likely to cite other patents from the same country than other countries.[32]

Another approach involves studying links between the inventive activities of different types of research environments. Approaches include studying the relationship between publicly supported research and private-research and between university research and industrial research more generally. Different uses of patent-based data (not just citations) in studying these relationships include the quite different studies of Narin (see below), Jaffe and Trajtenberg (1996) and Carpentier, Catherine & P. Templé (1995), Henderson, Jaffe and Trajtenberg (1995), Jaffe, Fogarty and Banks (1997).

4.3.Science & technology input indicator

Having investigated the application of citations for measuring knowledge spillovers between different areas of technical knowledge, this last section takes a look at involvement of science bases in technical innovation. This involvement or interaction is proxied by citations made between patents and Non-patent literature (NPL). In our computer-networking patent example, the relevant information is found under 'Other References'. Four items were cited by that patent, including a reference to the abstract of a Norwegian patent (PCT), reference to papers from two technical conferences as well as one journal article:

3.3. Other References
-PCT Search Report for International Application No. PCT/NO97/00096, Oct. 24, 1997.

[32] Jaffe A. & M. Trajtenberg. (1998) suggest that the likelihood is between 30-80% greater that a patent will cite other patents originating in the same country.

-Wakeman, I. et al., "Implementing Real Time Packet Forwarding Policies Using Streams,"Processing of the 1995 USENIX Technical Conference, Jan. 16-20, 1995 New Orleans, LA, USA, pp. 71-82.
-Khayata, R. et al., "A Distributed Medium Access Protocol For Wireless LANs," Record of the Asilomar Conference on Signals, vol. 1, No. Conf. 28, 1995 IEEE, pp. 238-242. ---
Kohda, Y. and Endo, S. "Ubiquitous Advertising on the WWW: Merging Advertisement on the Browser," Computer Networks and ISDN Systems, vol. 28 (1996), pp. 1493-1499.

The basis of such an approach was pioneered by Carpenter, Cooper & Narin (1980) in identifying science intensive areas of technology, and followed up notably by the Narin et al. and by the ISI group. Following parts of this literature, the general assumption is that the way patents make reference to NPL, especially scientific journals, can indicate knowledge transfer (i.e. spillovers) between typically 'scientific' knowledge and more typically technical applications. Schmoch[33] (1997) has for example recently studied the relationship between technology field and science via NPL links and found above average technology-science links for chemicals, micro-electronics and information technology.

The relationship between citing-patents and cited Non Patent Literature does offer a suggestion of a knowledge link but not necessarily a direct indication of science involvement in the citing technical field. It is therefore necessary to appreciate; that (i.) NPL citations can indicate less a link to science knowledge bases than a pragmatic link in the examination process and that we need therefore to differentiate the type of links made, and (ii) that second citations can, to the degree to which they do indicate scientific linkages, distort such links. We must be aware that the citation/patent might inflate the true nature of the links.

4.3.1. The examination process

What types of Non-patent literature (NPL) citations can reflect scientific knowledge flows? Consider first why NPL is used in the examination of patent application. Grupp and Schmoch indicate that such citations are not systematically used in the examination process. In their study, they found that examiners use NPL in clearing patent applications for several reasons.[34] A main motivation for using this kind of reference is that the patent's prior art cannot be investigated by reference to patent documents and NPL is resorted to in order to establish novelty and/or degree of inventiveness. Reasons for this may be that -

[33] Schmoch, Ulrich. Indicators and the relations between Science and Technology. (Scientometrics 1997)
[34] Greg Aharonian's service PAT-News has observed for ex. that those filing software patents deliberately avoid citing prior-art, thus influencing the citations that are found by the Examiner.

1. Patents do not cover the area and non-patentable research results become central to establishing novelty. The examiner has no recourse to patents and must therefore cite NPL.
2. The specific area in question is evolving so quickly that the lag in published patent documents from foreign patent offices prohibits reference to relevant patents. In this case, primarily the inventor's own published scientific papers are used.
3. A company has earlier published its results in a journal (perhaps its own) to protect novelty instead of pursuing a patent. Subsequently, patents that are sought drawing on the idea(s) published in the journal. Conference-proceedings can also be relevant in this connection.

Another problem that NPL is used to solve in the examination process are those cases in which prior-art exists in the form of patents, but such patents cannot be referenced because of language barriers.

4. Reference to Japanese language patent documents is difficult, and the examiner therefore uses an English abstract service. In reality the reference is to a patent despite the fact that the reference is in form of a publication

A last case where NPLs come into play is that where the prior-art is not patentable, though essential to establishing novelty and/or degree of inventiveness.

5. The reference is to an idea that is itself not patentable, but nonetheless essential to the patent application in question. The examiner cites reference books (e.g. an encyclopaedia) to establish the relationship.

The most robust connection between Non Patent Literature and the Scientific involvement in technical innovation is therefore to be found in the second motive listed above (i.e. that publication gap in patents is significant given the pace of change in the sector). Citations made based on motive 4 and 3 are least relevant as indicators of spillovers from scientific research. In addition to journals, however, reference books and other books can also be a clear pointer to flows emanating from scientific sources. It is therefore often most interesting to study citation patterns involving journals as well as books as indicators of science-technology links.

4.3.2. Distortion

In examining patterns, however, a second caveat should be mentioned. This is that the link to scientific knowledge bases can be distorted in the citation profiles. Especially one should be weary of the inflating effect of multiple citations by individual patents. Grupp, Reiss & Schmoch (1990) indicate that frequency of reference is not necessarily an indication of scientific intensity, but that individual patents with large NPT citation trails can destabilize the

citation populations. In this study, however we do not attempt to correct for this effect. Having investigated the citations to journals in this light, the number of citation a patent cites does indeed correlate with the types of knowledge the patent draws on.

5. CONCLUSION

This chapter has presented a critical discussion of the basis and background for using patent-statistics as an innovation indicator and reviewed some of its past and current applications. We have explored some of the unique advantages that have long recommended the use of patent-data as a technology indicator and we have noted that the increasing ease of access to such data together with more recent analytical approaches— notably Systems theories of innovation— have given it new relevance and new currency. The report has illustrated that patents include much more information than simply names of agents and technical classifications and that the information they hold in the form of citations is a particularly rich source. Possibilities here have not been exhausted. But there are many considerations to keep in mind when using patent data in general and citation-data in particular and some of these have been thoroughly surveyed here. In conclusion then, patents are a ‘tried’ indicator both of technology output of flows of inputs and intermediary innovative components. It is not a ‘true’ indicator, in the sense that there are many difficulties with its use, but it remains a viable and certainly promising indicator.

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V. Bibliometrics

Aris Kaloudis

1 INTRODUCTION

Bibliometrics is more than the mere counting of publications. Bibliometrics is a set of analytical concepts and methods for measuring the regularities, the structure, the dynamics, the performance and the institutional setting of written knowledge production in the research system. Bibliometrics is also a tool for situating the research efforts of a country in relation to the world, the research of an institution in relation to other institutions, and the research of scientific groups in relation to their own communities (Okubo Y., 1997).

1.1 Background

The term ‘bibliometrics’ was introduced by J. Pritchard in 1996. Pritchard defined bibliometrics as ‘the application of mathematical and statistical methods to books and other media of communication’ (see Pritchard J., 1969). Concurrently, Nalimov and Mulchenco introduced the term ‘scientometrics’ which they defined as ‘the application of those quantitative methods which deal with the analysis of science viewed as an information process’. Despite the different definitions, these two terms are today more or less synonymous and, in the following, we shall use them as such. Meanwhile, the term ‘informetrics’ has come to replace the originally broader speciality of bibliometrics as the science of books and other media of communication (European Commission, 1997, p. 111).

Bibliometrics is mainly a field of empirical research entirely dependent on electronically processed bibliographical databases and on methods (and software) of manipulating the retrieved data sets. From this point of view, the most important technological innovation for the development of the field has been the creation of Science Citation Index (SCI) by Eugene Garfield in 1963 in Philadelphia, USA. Garfield’s initial idea was to develop a quick and effective tool to identify published scientific articles for researchers. The innovative thing was the creation of a Citation Index which registered not only the bibliographic information needed for the identification of a paper but also the citations a paper gives to other scientific

work in its reference list. Thus, SCI became the most important database for bibliometric studies.

Concurrently with the creation of SCI, a new generation of bibliometricians emerged with the desire to build the foundations of a new scientific field: the 'Science of Science'. The most important figure, who systematically worked towards the theoretical foundations of bibliometrics as the 'Science of Science', was the physicist Derek de Solla Price. In his book 'Little Science, Big Science' from 1963, Derek de Solla Price advocates that science could be measured by its publications, and that the basic rules and forces governing scientific production could and should be analysed independently of scientists (Price D., 1963).

It has taken a long time for the bibliometric approach to gain acceptance as a measurement of the output of science. In the last decade, however, bibliometrics has become a standard information source for research policy and research management. Almost all compilations of science output indicators (e.g. national indicators of Science and Technology) rely heavily on publication and citation statistics. Bibliometrics has also increasingly been oriented towards the development of indicators to reveal the strengths and weaknesses of the performance of national systems.

Bibliometrics is, however, not only a diagnostic tool for monitoring national scientific performances. Bibliometrics is a discipline in its own right. There are today at least 4 research areas centering on different aspects of ' Science of science'. These are structural, dynamic, predictive and evaluative bibliometrics. Structural bibliometrics aims at mapping the epistemological structure of a scientific field based on co-citation and co-word analysis. Dynamic bibliometrics is the study of the dynamic properties of research production, such as, the growth and obsolence of a scientific field, life time of publications etc. Dynamic models of scientific production can be applied to make predictions about possible trends and the evolution paths of research.

The engine for the rapid development of bibliometrics in the last decades is to be found, however, in the increasing demand for complementary evaluation techniques (in addition to traditional peer reviews) in modern research policy making. Evaluation, and monitoring render bibliometrics an important tool in research policy. In fact, there has been a great research effort towards the improvement and refinement of bibliometric methods for

supporting both the evaluation and monitoring of research (see for example A.F.J. van Raan, 1993 and Moed H.F., 1992). Even so, there is a lot of work still to be done in this area. Bibliometric methods have to be developed and refined still further in order to gain greater confidence within the community of researchers and of research policy makers.

1.2 Content of the Chapter

In this chapter we do not pretend to provide an overview of the overall bibliometric field. This is not a task for a chapter in a report of this kind. The purpose of this chapter is rather to present a Guide for Policymakers in which we shall:

- present the basic concepts and issues in bibliometric jargon and methodology
- review the most commonly used bibliometric databases and discuss some analytical problems related to their strengths and weaknesses.
- present an overview of the most commonly used bibliometric indicators: we shall discuss their methodological limitations and we shall provide some examples of how bibliometric indicators can be used in decision making processes.

We distinguish between three main sets of bibliometric indicators. The first set is the indicators of scientific activity based on absolute or relative counting of publications. These are the most common bibliometric indicators. The second set of indicators is based on citation counting, such as the number of citations of the work of a research group or of a nation within one or more scientific fields. These type of indicators are often used as proxy of ‘scientific quality’. Relative citation indicators, citation analysis of scientific journals and indicators of ‘scientific excellence’ (high impact papers, high impact journals) also belong to this set of indicators.

The third set of indicators (and techniques) is made up of the so-called relational indicators which measure and map interaction patterns in the research system. Some relational indicators are: the number of acts of co-authorship (as a proxy for measuring the collaboration activity in a field), patterns of co-citations, patterns of co-authorships (for the identification of research networks in a field), co-word analysis (for the identification of the network of documents within a specific research topic), and patent citations to scientific literature (as a proxy for measuring the interactions between science and technology.)

The chapter is divided into 6 sections. Section 2 introduces some of the basic concepts of bibliometric analysis. Section 3 presents the most commonly used bibliometric datasources, namely SCI and other databases produced by the Institute of Scientific Information (ISI). Other bibliographic databases and on-line retrieval possibilities for bibliometric purposes will be discussed very briefly. In section 4 we provide an overview of the first (based on counting publications) and the second (based on counting citations) type of bibliometric indicators and their common uses. Section 5 discusses the bibliometric relational indicators measuring interactions in the research system. 'Mapping' is, thus, a key-word here. Mapping interactions in research is more than a construction of output indicators. From this point of view our overview departs from the presentation of traditional indicators and shows that other types of information can be used as 'indications' of complex relationships.In section 6 we discuss some ethical aspects related to the usage of bibliometric indicators: we conclude with a discusion of the challenges for the future bibliometric research.

This chapter is based on previous work done by many different bibliometric groups in USA and Europe. Some of the most influential of these groups are:

- CHI Research: Computer Horizons Inc., New Jersey, USA
- CWTS: Centre for Science and Technlogy, Leiden Univeristy, Netherlands
- FhG-ISI: Fraunhofer Institute for Systems and Innovation Research, Karlsruhe, Germany
- ISI: Institute for Scientific Information, Philadelphia, USA
- ISSRU: Information Science and Scientometrics Research Unit, Budapest, Hungary
- RASCI: Research Association for Science Communication and Information, Berlin, Germany
- OST: Observatoire des Sciences et des Techniques, Paris, France
- SPRU: Science Policy Research Unit, University of Sussex, Brighton, UK

The main references on which this chapter relies are:

- Okubo Y., 1997: An OECD-report, intended to be a manual, presenting the essential elements of bibliometrics and its application to the analysis of research systems. It is explicitly oriented towards bibliometric indicators with examples. In many respects, it is a very good introduction for policy makers to the field of bibliometrics.

- Callon M. et al., 1993: A clear, concise and popularised overview of bibliometric methods and applications for the lay-man.

- Moed H. et al., 1992: presents an overview of the state of the art in bibliometric Macro-Indicators.

- van Raan A.F.J., 1993: a clear, rigorous discussion about the basic principles in bibliometric research, with examples of how to use bibliometric indicators and analysis.

Other important references are:

- Egghe L. and R. Rousseau, 1990: A course book in library and information sciences with a systematic and logical presentation of theories and methods in bibliometric research.

- A.F.J. van Raan, 1988: A handbook of quantitative studies of Science and Technology presenting a wide range of topics in the field - theory, methods and techniques and applications of quantitative studies of Science and Technology in general (not only bibliometrics).

- Proceedings of the International Conferences on Science and Technology Indicators from Leiden (14-16 November 1988), Bielefeld (10-12 June 1990), Leiden (23-25 October 1991), Atwerp (5-7 October 1995) and Hinxton-Cambridge (4-6 June 1998).

- Proceedings of the Erasmus Workshop on Quantitative Approaches to Science and Technology Studies, Amsterdam (21-24 May 1996).

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2. BASIC CONCEPTS OF BIBLIOMETRICS

Bibliometric indicators are aggregate statistics derived from scientific literature. A principal assumption underlying the use of bibliometric indicators for measuring research output is that researchers publish their main research results in publicly available literature. Thus, one may

construct a picture of scientific activities from a quantitative analysis of scientific texts (Moed H et al. 1992, p. vii).

The basic information unit in bibliometrics is, therefore, the scientific paper. Of course, there are many other publicly available written forms of scientific output, such as books, handbooks, working papers, official reports etc. Quantitative analysis of these forms of publication activity is, however, a difficult task, mainly because there are no databases of universal standards of how, where and when to gather information on these types publications on a national or supranational level. Scientific papers, on the other hand, are registered and catalogued in many different international databases which can be used for bibliometric purposes.

Hundreds of thousands of scientific papers are published regularly in scientific journals. These journals are either multidisciplinary or specialised, international-oriented or focused on national (regional) readerships. Scientific journals have their own editorial policies and their own (often strict) quality controls. Some journals are more popular than others, or more influential than others. Some journals operate in research areas of rapid growth, others operate in research areas of constant or even diminishing importance.

2.1 The anatomy of the scientific paper

We distinguish between three major types of components in a scientific paper. These are: 1) the identification markers of the paper, that is, title, authors, journal in which the paper is published, affiliations, acknowledgements; 2) the main text with its characteristic structure (including use of abstracts, special languages, key words and references); 3) illustrations, photographs, tables, graphs and mathematical equations. All these elements represent possible data sources for quantitative and qualitative bibliometric investigation. In fact, some efforts have been directed towards understanding qualitative and quantitative aspects of the components of scientific papers and their interrelations (Callon M. et al. 1986, Mullins N., et al. 1988, Leydesdorff L., 1995, Seglen P., 1996).

For the construction of common bibliometric data, however, the important information in a publication is: what kind of publication it is (note, editorial, scientific article, review etc.); its title; its list of authors; institutional affiliations (author addresses); key words; references;

publication year; and journal specific information (title, volume, number, number of pages etc.).

Title of the paper: The title, along with the abstract and keyword list, refers to the content of the paper rather than to the author. The registration of titles serves in searching the literature for papers on specific topics by using certain words or word combinations in the search. Many bibliometric analyses rely on the combination of title terms and other information items such as name of authors, citations etc. (see for example Griffith B.C. and H. Small, 1974).

Author list: We can observe the trend towards increasing numbers of (co)authors per paper, especially in the natural sciences. The listing of authorship is an important function as it signals a 'property right' on the published material. Thus, researchers can accumulate 'property' units, i.e. papers under their authorship, and bibliometricians can measure individual scientific productivity by counting papers. Authorship of a scientific paper also provides an effective mechanism by which a work can be reported and indexed. The designation of article authorship allows scientists to efficiently research the past works of others through both citation and co-citation analysis. Another important bibliometric use of the authors' list is the construction of author networks, or co-authorship networks. Based on the co-occurrence of author names in the author lists of a set of papers, it is possible to draw maps of collaboration patterns between the identified authors in the selected set of papers.

Institutional affiliation: With the increasing professionalisation of science, scientific papers began to appear with a clear indication of the institutional affiliation of the authors. This supplies the reader with the address of the authors. In many cases, information on institutional affiliation is more critical than information on authors. For example, it is often the case that students publish papers with their name as the first author and the name of lab director as last author of the list. In some bibliometric studies it may be more crucial to investigate which laboratories have been involved in the creation of a set of papers than who were the authors of the paper.

Institutional affiliation also provides indispensable information for the construction of bibliometric macro-indicators. Without the authors' addresses it is very difficult to determine in which regions, geographical areas or countries a paper has been produced. Thus, national indicators of scientific publication rely almost exclusively on this information.

Another important bibliometric use of institutional affiliation lists is the construction of collaboration networks between labs or, generally, between research institutions (see for example Kaloudis A., 1995). Two or more research institutions are listed together as the authors' institutional affiliations in more than thirty per cent of the publications in modern science and technology. Based on the co-occurrence of institutional affiliations in a selected set of papers, it is possible to draw maps of collaboration patterns between the institutions identified in the set of papers.

Journal related information: This is crucial information for the identification of a scientific paper. Journal name serves also in some subject classification systems as a means of classifying papers under disciplinary categories. These categories are defined by collections of journals (this is for example the case in the classification system of ISI - see section 3).

References, citations: A scientific paper does not stand alone. It is embedded in the literature of the research subject it treats. Therefore, almost all papers, notes, reviews, corrections, and letters contain a reference list. Each reference is a citation to another document (other paper, book, report etc.). Citations contain information about title, author, where and when the cited document was published.

2.2 Citation indexing

A Citation Index is a reference tool that presents bibliographic data on published journal articles. What distinguishes it from other bibliographic indexes is that it includes all the cited references (footnotes or bibliographies) published with each article. These cited references are links to prior and relevant research established by the publishing authors themselves.

The introduction of the Science Citation Index (SCI) in 1964 was the first large-scale attempt to apply the citation-indexing concept to the problem of searching the scientific literature. The Institute for Scientific Information (ISI) is today the publisher of the Science Citation Index® and other databases of scholarly research information in the sciences, social sciences, and arts & humanities. In ISI's databases, all references listed in the articles included in the selected journals are indexed. This makes possible the construction of the component of SCI which distinguishes it from other databases, that is, the Citation Index .

The SCI Citation Index connects the list of all the publications contained in the covered journals (source items) with the past publications (target items) they have cited in their reference lists. The Citation Index is organised alphabetically by cited author, using the last name of the first author. Under each cited author are listed chronologically the items that have been cited in the reference lists of source publications and the source publications. This connection makes possible the performance of many different types of citation analysis.

2.3 Citation analysis

Citation analysis is the set of methods and techniques for the measurement of the relations between cited and citing documents. The fundamental hypothesis behind citation analysis is that most of the scientific ideas that have been regarded as important or influential can be associated with one or more scientific works that are at certain time highly cited. Sometimes recognition through citation frequency comes soon after the publication, but a two to three-year time lag is the norm. Papers containing important ideas will nor necessarily continue to be highly cited for all time. Usually, new papers will supersede the original ones by reformulating ideas, issues etc. in a more up-to-date language.

Highly cited papers do not contain only ‘important ideas’. Papers become highly cited mostly because they report about important methodological breakthroughs, new procedures and data compilations. The word ‘important’ should not be confused with ‘correct’. There are several examples of highly negative cited papers in areas of research. Like ‘quality’, ‘importance’ in research is undoubtedly a highly complex matter. Citation statistics cannot lead to an absolute scale of importance. Citations can only give an operationalisation of the notion so that we can present a measure of ‘importance’ or ‘attractiveness’ of a publication. This makes it possible to answer tentatively questions such as: ‘What are the most important advances in your speciality in the last few years’ or ‘How would you rate the quality of a paper on a scale from 1 to 10?’

Research into the development of reliable citation metrics has been intensified in the last 20 years (Schubert, A., 1995). The main questions explored in these efforts are: is a citation indicator a sufficient indicator of research impact? Is the average number of citations per unit

(a researcher or a department) a better indicator than simple citation counting? What normalisations should be established for different disciplines?

In relation to the last question, we know that there is a great variation in the number of average citations per paper between different disciplines and in many cases between different subject areas within the same discipline (see for example Schubert A., 1996).

Impact factor

As an attempt to avoid some of the analytical problems related to the questions raised above, the concept of 'journal impact factor' has been introduced in citation analysis. The impact factor of a journal is a measure of the frequency with which the "average article" in the journal has been cited in a particular year or period. The impact factor for a journal is a ratio between citations received during the year and the citable items (the journal's publications) published in that period. Thus, the impact factor of a journal is calculated by dividing the number of current year citations by the source items published in that journal during the previous two years.

Example of calculation of impact factor (based on Garfield E., 1994):

A= total cites to the journal X in 1996

B= cites in 1996 to articles published in the journal X in 1995 and 1994 - the two previous publication years (B is a subset of A)

C= number of articles published in journal X in 1995 and 1994

D= journal X's impact factor for 1996 = B /C

The impact factor is useful when one needs to compare different journals. It eliminates some of the bias of absolute citation counts which favour large journals over small ones, or frequently issued journals over less frequently issued ones, and of older journals over newer ones. It is clear, for example, that all things being equal, the larger the number of previously published articles, the more often a journal will be cited (Garfield E., 1994). The impact factor bypasses these shortcomings in the counting of the absolute citations of a journal and introduces the possibility of comparing journals.

In section 4 we discuss the applications of the impact factor for the construction of bibliometric indicators and the methodological problems connected with this.

Research on highly cited papers shows that the number of such papers is relatively small compared to the number of all papers produced in a research field. It is estimated that only one per cent of all papers receive 10 citations or more in a particular year (Garfield E. et al., (1978), p. 182). This means that only few seminal works exist for any single speciality and that the normal turnover in highly cited works from year to year - that is, the appearance of new cited works and the disappearance of old ones - may reflect the rate of change of scientific issues in a research field. In other words, citation is also an indicator of a paper's 'importance' or timeliness for a particular historical period in the evolution of a research area. Why a paper attracts such attention is, however, a matter of the investigation of the paper's conceptual and social relations.

2.4 Bibliometric distribution laws

Only a very limited amount of papers attract a huge number of citations. This 'skewness' in bibliometric distributions is also observed in many other quantitative measurements of research. Egghe and Rousseau, 1990, introduced the concept Information Production Processes as a generic term for the presentation of a family of empirically proven scholastic laws which govern distribution processes in science and technology. These laws are known as Lotka's law, Zipf's distributions, Mandelbrot's law , Bradford's law to name but a few. It has been mathematically proved that, within a specific theoretical framework, several of these laws are equivalent (Egghe L. and R. Rousseau, 1990, Chs. IV.4 and IV.5). This means that the laws describing research production activities are manifestations of the same fundamental principle.

Indeed, these laws describe cumulative advantage processes in scientific production. An example of cumulative advantage processes in research is the fact that a paper which has been cited many times is more likely to be cited again than one which has been little cited, or that an author of numerous papers is more likely to publish again than one who has been less prolific. Cumulative advantage processes in science is also known as 'success breeds more success' phenomenon or 'Matthew effect'.

Derek de Solla Price (1976) was one of the first who systematically attempted to provide a formal explanatory platform of 'success breeds more success' processes. The success-breeds-success argument actually refers to the deeply dynamic nature of knowledge processes and to their sensitivity to initial conditions. There are many unanswered questions related to these regularities. Yet, Information Production Processes laws offer a theoretical platform (Egghe L. and R. Rousseau, 1990, Ch. 4) on which we can schematise expectations and calculate predictions about productivity patterns.

2.5 Levels of bibliometric analysis

The expertise of scientific peers is mainly related to the assessment of the quality and performance of certain research units, research fields, or specialties. This is an assessment of research quality and performance on the meso- or micro-level. National science and technology indicators, on the other hand, represent information of a broader scope, on the macro-level.

Bibliometric analysis at the macro-level have been extensively applied in:

- Evaluations of the effectiveness of national science policy schemes
- Overviews of national activities in various scientific fields (see for example Kaloudis A., T.B. Olsen, 1998)
- Assessments of strengths and weaknesses of national research performance in an international context (see for example European Commission, 1997, pp. 168- 171)
- Identification of the structure of relevant scientific research areas, particularly new emerging fields of strategic importance (see for example Persson O., 1998).

Bibliometric analysis at the meso-level has been successfully applied in the context of peer evaluations for the assessment of institutional performances of research units in university departments (see for example Moed H.F., 1998), in evaluations of public research organisations (several examples in Scandinavia and elsewhere) and in evaluations of research programmes (see for example Hagen I., A. Kaloudis, E. Sjønnesen, 1997).

At the micro-level, that is at the level of individual researchers, research groups or research projects, there are some examples of bibliometric analysis being successfully applied for evaluative purposes (see for example Moed H.F. and A.F.J. van Raan, 1988 for the

presentation of evaluation of university research groups and G. Lewison, R. Cottrell, D. Dixon, 1998 for the description of evaluation processes in Welcome Trust foundation for the selection of exceptionally good scientists). Despite these examples, the application of bibliometric techniques are generally not recommended at the micro-level because of the many pitfalls and shortcomings of bibliometric techniques in small publication samples.

In sections 4 and 5 we shall present the most common bibliometric indicators applied both at a macro- and meso-level bibliometric analysis.

3. BIBLIOMETRIC DATASOURCES

The source for bibliometrics is always a database. A bibliometric analyst utilises computerised databases containing bibliographic information on scientific publications, and intelligent software to analyse those databases. These databases are made publicly available either in a CD-ROM version, or through host computer organisations offering remote access facilities (Moed H.F. et al., 1992).

Generally speaking, the majority of the existing scientific literature databases are only partly suitable for bibliometric analysis. There are three main reasons for this. First, bibliographic databases are designed for information retrieval, but they are not immediately appropriate for bibliometric use. Thus, databases do not always contain necessary information for the construction of bibliometric indicators. For example, there are few databases in which authors' institutional affiliation addresses are registered. Second, the coverage of the databases may not be good enough for certain types of bibliometric investigations. Third, the information included in the databases is often not 'standardised', that is names of institutional affiliations, countries, etc. in the databases are not always reported in a standard way.

Lack of 'standards' in bibliometrics

In fact, there is a more general need for common standards of data processing and methods in bibliometric research. Different database versions and a variety of applied methods and techniques result occasionally in considerable deviations between the values of science indicators produced by different bibliometric research groups. Such deviations are observed even in studies in which the same database has been used (see for example the discussion in

Glänzel W., 1996). In short, bibliometric data produced by different institutes must not contradict. This is not always the case today.

Problems of subject classifications

A problematic task in bibliometric research is the application of different criteria for the definition of field or subfield categories. This is an important issue especially in those cases of bibliometric research where quantitative information about national (or regional) performances in scientific fields is provided.

Field and subfield classifications of scientific publications are generally based on the definition of adequate sets of journals. The most widely used field classification schemes based on journal classifications are those produced by the Institute for Scientific Information (ISI), and the Computer Horizon Inc. (CHI).

It is known, however, that there are several methodological drawbacks with journal based classification methodologies. The unit of bibliometric information is, after all, the scientific paper and not the scientific journal. It is, therefore, the information based on the scientific paper and not the information on the scientific journal which should determine the paper's subject(s) classification.

Even when sets of research journals are the determinant factor for subject classification, different bibliometric groups often chose opposing definitions of journal sets for the classification of more or less the same topics (see the discussion in Glänzel W., 1996, p. 169).

A second problem in this matter is the multidisciplinary nature of journals. Many journals operate at the intersection of traditional disciplinary fields, or they publish work both in basic and applied research or work at the intersection of applied research areas. Thus, it is not a straightforward affair to attribute publications in multidisciplinary journals to categories based on traditional disciplinary definitions.

A third problem emerges in the analysis of bibliometric time-series constructed upon fixed-journal-set subject classifications. Even slight modifications of journal sets from one year to another can result in heavy distortions and incommensurabilities. When such modifications occur one has to recalculate all publication and citation statistics for the whole time period

based on the new and modified journal sets of subject classifications. This is how ISI updates annually the bibliometric statistics provided in its National Science Indicators database (see also below).

In general, there are few examples in bibliometric literature where new methods of subject classification have been introduced. Katz S., D. Hicks, 1995, in the Science Policy Research Unit (SPRU) developed ISI's classification system by constructing a hierarchy of broad interdisciplinary journal categories. This classification system has been tailored for a sectoral analysis of UK publications. Also Glänzel W., A. Schubert, H.J. Czerwon, 1998, presented a new method where the list of references of papers published in multidisciplinary journals, such as 'Nature', or other general journals, such as 'Lancet' can be used satisfactorily as a criterion for their subject classification. This method further contributes to the improvement of ISI's classification system.

3.1 Institute for Scientific Information (ISI) - databases

ISI was founded in 1958 by Dr. Eugene Garfield and is headquartered in Philadelphia, Pennsylvania, USA. ISI produces general information tools for the research community (for more information about ISI, see http://www.isinet.com).

What are particularly relevant to bibliometric research are ISI's three citation databases which index more than 8,000 journals cover-to-cover, including bibliographic data of publications, abstracts, and cited references.

These three databases are:

- Science Citation Index (SCI), covering approximately 5,600 scientific and technical journals in a broad range of disciplines.
- Social Sciences Citation Index (SSCI), covering more than 1,700 social sciences journals.
- Arts & Humanities Citation Index, covering more than 1,150 arts and humanities journals in a broad range of disciplines, and individually selected items from over 7,000 social sciences and humanities journals.

Some scientific journals disappear, other change names or merge and of course new journals emerge. ISI monitors these changes and regularly updates the list of journals covered especially by SCI. The annual turnover of journals is about 7 per cent of the total. The criteria

for the inclusion of new journals in ISI's databases are: timeliness of publication, English language article titles, abstracts, and keywords, application of peer review process for the acceptance of publications, and a high journal impact factor.

Science Citation Index (SCI)

Some of the advantages of the SCI has been summarised in the review report on the 'State of the Art' of bibliometric macro-indicators prepared by The Centre for Science and Technology Studies (CWTS) at the University of Leiden for the European Commission in 1992. In this report Moed et al. concluded that the SCI is the most appropriate database for the construction of bibliometric indicators. There are three reasons for that. First, SCI is the only database covering the natural and life sciences with information on citations. Second, SCI is one of the very few databases containing complete information on the institutional and geographical affiliations of all publishing authors. Third, SCI covers the most widely used, recognised and influential scientific journals in the world. In other words, SCI limits its scope of coverage to world-class scientific journals representing the 'core' production in research fields of the Natural and Life sciences.

However, there are also some problems in the usage of SCI that deserve careful attention. First, since SCI is a multidisciplinary database there is a problem of rigorous definition of scientific subfields. Each year, the Current Contents version of ISI provides a list of all the SCI journals and their field classifications. ISI's classification list is widely adopted for the construction of national bibliometric indicators worldwide. Yet, there are several weaknesses in ISI's subject classification scheme (see also the discussion above in 'problems of subject classification').

Second, there are indications that SCI favours Anglo-American research. Journals publishing in English are more likely to be included in SCI than non-English language journals. For example, there are reasons to believe that important non-English language journals in Europe may not be covered by the SCI for this reason (Moed H.F., 1992, p.x).

Social Science Citation Index (SSCI) and Arts & Humanities Citation Index (AHCI)

SSCI is not as important a bibliometric datasource for the measurement of social sciences as SCI is for natural and life sciences. Because of the more national orientation of research in social sciences and humanities they are indications that the use of SSCI may lead to serious

biases, especially when it comes to evaluation of national (non-English) research performance. Also, other 'technical' and more substantial questions concerning the coverage of international social science research reduces the reliability of bibliometric indicators based on SSCI and AHCI. Despite these problematic aspects of SSCI, there is an increasing number of serious studies using SSCI as their main datasource (see for example Glänzel W., 1996, Nederhof A.J. and E. van Wijk, 1995).

Other products from ISI relevant to bibliometric research

It is worth mentioning some other products provided by ISI:

- Subject specific Citation Indexes, such as the Biochemistry & Biophysics Citation Index(TM), Biotechnology Citation Index(TM), etc.,
- Journal Citation Reports - mainly a list of journal impact factors within subject categories
- Specifically designed research performance and evaluation datasources such as High-Impact Papers (diskette database of the most influential papers in specific fields), Journal Performance Indicators (an electronic database of journal statistics consisting of publication and citation data on the journals indexed by the Institute for Scientific Information), National Science Indicators (contains only the number of ISI-indexed papers from each nation and the number of times the papers were cited through 1997), Research Fronts (contains bibliographic and citation information on some 20,000 clusters of related research papers) and others.

3.2 Other databases

Apart from SCI database, the most widely used bases for bibliometric purposes are:

- Chemical Abstracts: A database in Physics and Chemistry produced by Chemical Abstracts Services, for the American Chemical Society. It records an average of 500,000 items annually, from about 10,000 journals.
- Compenex: An Engineering and Technology database produced by Engineering Information, USA. It records an average of some 150,000 items annually, from about 4,500 journals.
- Embase: A database in medical sciences produced by Excerpta Medica, Netherlands. It records an average of 250,000 items annually from about 3,500 journals.

- Inspec: A database in Physical sciences produced by the Institute of Electrical Engineers, UK. It records an average of 200,000 items annually from about 2, 200 journals.
- Medline: A database in medical sciences from the National Library of Medicines, USA's (NLM) premier bibliographic database. The database contains approximately 9 million records dating back to 1966 from about 3,900 bio-medical journals.

When it comes to patent databases the most frequently used are the Derwent Information Limited databases and that of Computer Horizon (CHI). In this chapter, however, we shall not focus on patent bibliometric indicators which is the subject of Chapter 3, 'Patents and Inventions'.

3.3 Bibliometric on-line datasources and techniques

On-line retrieval techniques have been applied in several bibliometric studies (see for example Persson O., 1988, Moed H.F., 1989, Hjortgard Christiensen F., P. Ingwersen, 1996).

On-line techniques may be applied for macro-, meso-, and micro bibliometric studies (for an example of a macro on-line bibliometric study see Ingewersen P. , 1998). The most critical phase in an on-line bibliometric search is the precise formulation of criteria for the identification and retrieval of a correct set of publications.

The advantage with on-line bibliometrics is that one does not have to pay for a permanent (on-line or of-line) access to a database. One pays only for the information retrieved in the on-line searches. On the other hand, extensive bibliometric studies based on on-line information retrieval may prove to be a very costly affair.

Another advantage is that one may have simultaneous access to more than one database, such as SCI, INSPEC etc. through online vendors like DIALOG (produced by Knight Ridder Information). This provides the opportunity to validate bibliometric analysis by comparing the results obtained from the database. In general, developments in on-line bibliometric information processing is a promising area of future research.

4. STANDARD BIBLIOMETRIC INDICATORS MEASURING PERFORMANCE IN THE RESEARCH SYSTEM

We can distinguish three main types of bibliometric indicators: 1) size and characteristics of scientific output; 2) size and characteristics of scientific impact; 3) relational features of science. The first two types constitute the core of bibliometric research performance analysis, the research performance indicators.

The basic assumption behind bibliometric indicators is that bibliometric methods are appropriate when written forms of knowledge, in particular publications in journals and patents, are the principal carriers of knowledge. This assumption provides a common base for the measurement of the whole spectrum of research activities.

However, the role of 'written knowledge', and in particular of the scientific paper, is not the same for all fields of research, all countries or all research organisations (van Raan, A.F.J., 1993). Thus, inferences based on bibliometric statistics may be misleading in those cases where production and knowledge dissemination in research mainly take on other forms than the 'scientific publication' or the 'patent'. This occurs, probably more often in the world of technology than in science; it is more often the case in Development activities than in Research, and, perhaps, occurs more often in the non-academic loci of R&D activities than in universities.

4.1 Definition of performance indicators

Van Raan A.F.J., 1993, distinguishes between bibliometric indicators as one-dimensional or scalar indicators and multi-dimensional indicators. One-dimensional techniques are based on direct counts of bibliometric items, such as scientific papers or patents. Research performance indicators are mainly constructed using scalar techniques (relational indicators are the theme of the section 5 in this chapter).

Two important concepts play a central role in the development of bibliometric performance indicators:

- Production of knowledge, operationalised by the number and the type of scientific publications
- Impact of this knowledge, operationalised by the number of citations received by publications within a certain period of time. We may distinguish here between short-term impact (for example, citations counted in the first two years after publication) and long-term impact.

Performance indicators are the principal bibliometric tools for monitoring and evaluating research. The statistical nature of bibliometric performance indicators requires sufficient large populations of the counted items. Bibliometric assessments based on performance indicators are, therefore, more focused on the publication performance of university departments, research institutes, and research sectors such as private companies in a country at a meso-level; countries, regions and research (sub)fields at a macro level.

4.2 List of common performance indicators

The following research performance indicators are those most commonly in use:

P1. Number of publications:

Counting the number of the identified publications produced by the research unit under study (in the following we use 'research unit' as a generic term: by that we mean individual researchers or departments, universities, research institutions, countries etc.). This indicator is the most basic of all. It is recommended to construct a time-series for as many years as possible (in many cases at least 8 years is recommended). A longer time-series helps in the assessment of scientific production trends.

There are some general methodological issues concerning how one should count publications where two or more authors are involved. These issues are discussed in the next paragraph.

A simple indicator of a research unit's productivity is obtained if we divide the number of identified publications (P1) by the number of research personnel working in the research unit under study (or the equivalent R&D man-years). For the calculation of national or regional productivities, it is common to calculate the ratio of the number of a nation's publications in a given field per million of inhabitants. However, this indicator has been repeatedly criticised in the past. The main argument against population normalisations is that the size of the

population is not a relevant parameter in R&D production processes. Many critics advocate that it is better to use the number of researchers in the field under study instead of population statistics. On the other hand, measuring the number of researchers in a country (or a region) in a given field is neither a standard indicator nor a trivial task to calculate (see for example Table 8 in OECD, 1995).

P2. Number of citations per paper

Counting the number of citations received in the first two or three years after publication of the selected set of papers. The time period for which we count citations is called the 'citation window'. The aim is to construct as long a time-series as possible. This indicator measures the short-term impact of the set of publications selected, and serves for the assessment of impact trends. In cases of studies at the micro-level, it is recommended that self-citations and citations received from within the research group should be excluded (van Raan, 1993).

The methodological difficulties of this indicator lie mostly with its interpretation and not its calculation. We discuss this further below.

P3. Expected citations:

The average number of citations received by a paper published in the same journal, in the same year, and of the same document type (article, note, review, etc.). This statistic refers directly to a journal's impact factor. Expected citation statistics serve as a reference point for deciding whether the citations received by a given publication are numerous or not. Expected citations (and journal impact factors) is a standard indicator which has been used in earlier studies.

In some instances, expected citations may even substitute the observed (actual) number of citations. There are two main reasons for that. First, it is costly and labour-intensive to identify each and every citation to a given publication. This is especially the case when the database in use does not contain information about citations.

Second, there is a citation time-lag effect, since it typically takes two or three years to establish whether the publication is cited by others. Journal impact factors (or Expected Citation calculations) from previous years may serve as a predictor of the future actual citations the given publication will receive.

In some studies, Expected Citations is also used as an alternative indicator of ‘quality’. The idea here is that some journals are more influential than others. Since there is more competition between researchers to publish in the influential journals, and since it is harder to get papers accepted, publication in an influential journal is an indication of ‘good’ research in its own right. The influential journals tend to have higher impact factors (they are more cited, on average) than the rest. Therefore, high Expected Citations or impact factors may serve as an indicator of ‘quality’. Use of journal impact factors as a proxy of ‘quality’ has been criticised in the literature (see Seglen P., 1992). In the next paragraph we shall present the main strands of this criticism.

P4. Mean observed citation rate:

The number of citations received in the first two (or three years) after publication of the selected set of papers (P2) divided by the number of the selected papers. It measures the average impact of the selected papers and it gives an overall impression of their degree of ‘attractivity’.

P5. Mean Expected Citation rate:

This statistic is similar to the mean observed citation rate except that the actual number of citations received is substituted by the impact factor of the journals (average citation frequency to a paper in the journal) in which the selected paper was published. ‘Mean expected citation rates’ are occasionally preferred to ‘mean observed citation rates’ for the same reasons explained in (P3) Expected Citations.

P6. Relative Citation Rate (RCR):

Relative Citation Rate is calculated as the mean observed citation rate divided by the mean expected citation rate (P3/P4). It provides a means to compare the impact of the selected set of papers with the average impact of papers published in the same journals in which the selected set of papers were published.

When the value of the relative citation rate is the unity (RCR=1), this is an indication that the set of papers under study are cited exactly at an average rate (as if all papers were an average paper of the corresponding journal). When the value of the relative citation rate is below unity (RCR<1), this is an indication that the citation rate of the assessed papers is, on average, below the expected. The opposite is true when RCR >1.

Methodological objections against this indicator are again related to the use of Mean Expected Citation Rate and, thus, journal impact factors (see the discussion in the next paragraph).

P7. Activity Index

In measurements of national performance a relative indicator of research activity may be calculated. It is known as the Activity Index (AI) (Schubert et al., 1988) and is defined as follows:

AI: The country's share in the world's publication output in the given field divided by the country's share in the world's publication output in all science fields,

or alternatively

The given field's share in the country's publication output divided by the given field's share in the world's publication output.

If the Activity Index of a country in a given field is above unity, this tells us that the country has a greater percentage of its overall paper production papers in this particular field compared with the field's share of the world's publication output. This again is an indication of a revealed specialisation in this particular field. It is important to bear in mind that no country can show high Activity Index in all science fields. If AI is above unity in one field it must be below unity in another field. Perhaps for this reason the Activity Index is often used for the identification of national research specialisation profiles (see for example the Second European Report on ST Indicators, European Commission, 1997, p. 167, 168, 169).

The definition of Activity Index can be modified for the study of regional publication activity or even for institutional publication activities as in the case of a comparison of universities for example (for more details on that and for a rigorous definition of the Activity Index of a university see Carpenter M.P. et al., 1988).

P8 Attractivity Index:

In measurements of the research impacts of national research systems, a relative indicator of impact may be calculated. It is called the Attractivy Index (AAI) (Schubert et al., 1988) and is defined as follows:

AAI = The country's share in citations given to its publications in the given field divided by the country's share in citations attracted by publications in all science fields

or ;

AAI = the given field's share in citations attracted by the country's publications divided by the given field's share in citations received by all publications in the world.

This indicator characterises the relative impact of a country's publications in a given subject field as reflected in the citations received by the country's publications in the given field. AAI equal to unity (AAI=1) indicates that the country's citation impact in the given field corresponds precisely to the world average, while AAI >1 reflects higher than average impact (that means that the country's share of citations in the given field is higher than the country's overall impact in all fields). The opposite is true if AAI in a given field is below unity.

As is the case with the Activity Index, the Attractivity Index cannot be above unity in all fields. If the AAI of some fields is above unity (AAI > 1), the AAI of some other fields will be below unity (AAI < 1). AAI can, therefore, be a useful measure when constructing national or institutional impact profiles.

AAI = 1 indicates that the country's citation impact in the given field matches exactly the world average. AAI > 1 reflects higher than average impact, AAI <1 lower than average impact.

One can combine Activity Index and Attractivity Index measures in two-dimensional graphical representations. The interesting thing about these graphic representations is that activity and impact strengths and weaknesses are revealed simultaneously and, thus, one can 'see' the performance profile of the research unit under study (country, university, etc.). An illustrative example of national performance profiles, or the combination of activity and impact (or attractivity) measures, can be found in the Second European Report on ST Indicators, European Commission, 1997 (European Commission, 1997, pp. 170-172).

Other measures of research performance

As already mentioned, the lack of standardisation between the work of different bibliometric groups leads to the adoption of different terms for the same indicators and to slightly different methods to calculate these indicators (for example different publication periods and citation windows, see Glänzel, W., 1996). But, there is a consensus that the indicators presented above are the standard performance indicators in bibliometrics.

However, other measures have also been applied in the past to measure performance aspects in research. Some of these are:

- Number of very 'high impact' papers: Statistics of very 'high impact' papers (that is exceptionally highly cited papers) may serve as an indicator of 'scientific excellence'. It has been used in evaluation of world research organisations, such as CERN (see for example Irvine J., B. Martin, 1984, p. 254, 257).
- Influence weight: An alternative indicator to journal impact factor. The idea behind this complex indicator is that, rather than counting citations to a set of papers individually, one instead uses the 'influence' of the journals in which they are published as a proxy measure of their impact. But the 'influence' of the journals is not based only on the average citations per paper in the journal (journal's impact factor). One calculates instead the weighted number of citations a journal receives from other journals. The weights give a citation from journals of 'high influence' greater importance (greater weight) than citations received by journals of lower influence. After the calculation of the weighted number of citations a journal receives from other journals, one normalises this weighted number of citations by the number of citations the citing journal gives. With this normalisation one takes into account the fact that papers (and, thus, journals) in some fields contain more references on average than those in others.

This indicator is quite complicated to calculate. It has been introduced in a study of bibliometric profiles for British academic institutions (for more details see Carpenter M.P. et. al. 1988).

All bibliometric indicators follow bibliometric distributions with certain statistical properties. This is not the place to present the theoretical backgrounds of statistical reliability calculations of performance indicators. For an introduction to this topic of bibliometrics we recommend the following works: Schubert A., 1988, Egge L., R. Rousseau, 1990, Chapt. 1 and 4 and Glänzel W., A. Schubert, 1993.

4.2 Important methodological issues related to performance indicators

The construction of the above-mentioned performance indicators leads to some fundamental methodological questions about the nature of bibliometrics. These are: how to count a publication; how to count a citation; what is the meaning of a citation count; how to use journal impact factors.

How to count and how to attribute credit?

Two main problems arise in counting publications. The first is what type of literature one has to include or exclude in the counting process. A typical database (as for example SCI) encloses several different types of literature: articles, notes, summaries, reviews, notices, discussions, proceedings, letters to the editor etc. Obviously, scientific articles must be included in the counting. But for almost all the remaining types of literature, there are no standards of what to include and what to exclude and the choice lies with the analysts. Okubo Y., 1997, refers to studies showing how easily bibliometric statistics can change depending on the types of literature chosen (see Okubo Y., 1997, p. 15, and Leydersdorff L., 1991).

The second problem is even more fundamental and relates to how to determine credit in a collaborative paper. Price (1976, p. 300) pointed out that there is no adequate model or theory for the attribution of credit in the case of multi-author collaborative papers. The same problem arises for the attribution of credit in the case of collaborations between two or more research institutions, or two or more countries. How then can the participation of authors in multi-authored publications be measured?

The are two main ways of assigning credit: either to assign full credit to all authors (that is, count ‘1' for each co-author) or to divide unity (full credit) by the number of authors (or institutions, or countries) and assign a fractional credit. Trenchard, 1992, suggested that within fractional counts, various weighting schemes are possible, such as giving the first author more credit. Yet, for policy makers whole counting statistics are more comprehensible and easy to interpret. In addition, some bibliometricians argue that fractional counting is an inferior procedure and that when the volume of data is substantial, equal counting of all authors is in most cases the best solution (see Okubo Y., 1997, p. 21).

Of course, the same problems arise when one counts and attributes citations to multi-authored papers. Again, full credit of citations is also the easiest and the widest technique in use.

What is the meaning of a citation count?

Why is receiving a citation a positive thing? And why is the accumulation of citations to a given article an indicator of the article’s impact, attractivity (or even quality) without knowing the citer’s motivation?

Egge L. and R. Rouseau, 1990, identified four basic assumptions underlying impact indicators (citation counts):

Assumption 1: Citation of a document implies use of that document by the citing author.

Assumption 2: There is a high positive correlation between the number of citations which a document receives and the quality of that document.

Assumption 3: Citations are made to the best possible works.

Assumption 4: The content of a cited document is related to that of the citing document.

Obviously there are many conceptual (and some technical) difficulties related to all these 4 assumptions. Yet, none of the studies in which these assumptions have been tested calls for their rejection (see the discussion in Egge L., R. Rouseau, 1990, pp. 224-227). What is clear, however, is that there are many technical and conceptual critical points against citation counts. Taken together, all these points argue for a prudent and careful use of impact indicators.

How to use impact factors?

The main argument against an uncritical application of the journal impact factor as a proxy of a given publication's actual impact has been formulated by Per Seglen, 1992. He stated that "The journal impact factor (the mean citedness of a journal's articles) is a characteristic journal property that stays relatively constant over time. However, within each journal the citedness of the individual articles form an extremely skewed distribution, regardless of journal impact." (see Seglen P. 1992, p. 143). In other words, it is not true that journal status, as measured by journal impact, contributes to article citedness independently of the properties of the given article. This implies that for small article samples one has to calculate the actual citations and not their expected citation derived by the impact factor of the journals in which they are published.

4.3 Performance indicators: to conclude

We have listed 9 basic performance indicators. These can be used for diagnostic and evaluative reasons. These indicators should be used cautiously, particularly in evaluation exercises. It is advisable to use several impact and activity indicators together. Performance

indicators reveal different features of the complex relations behind the research activities under study. Their combined results offer a more nuanced analysis than the individual indicators.

5. RELATIONAL BIBLIOMETRIC INDICATORS / MAPS OF SCIENCE

5.1 Definition of performance indicators

In contrast to performance indicators, relational indicators are not scalar. They are not simple metrics. They are designed to represent structural and dynamic aspects of the research system and they are, often, cartographical representations and not indicators in the traditional sense.

The advantages of such cartographical representations are multiple. First, a visualisation of complex masses of data provides a more complete overview in less time. Second, it is more easily remembered. Third, properly constructed it provides a structured reduction of huge amount of information. Fourth, a map is a representation of a static structure. It is, however, possible to construct a series of maps for investigating dynamic features of science. Examples of such dynamic features are changes in collaboration patterns between researchers or changes in thematic orientations in research fields.

Some of the disadvantages with cartographical representation of data are:

- General bibliometric methodological and conceptual limitations discussed already (see section 4).
- Methodological and conceptual limitations concerning the nature of bibliometric maps (what does a bibliometric map actually tell us?). These, are discussed in paragraph 5.7.
- The use and applicability of bibliometric mapping in general, presupposes validation feedbacks from experts. However, experts who want and can give detailed comments on the maps and additive tools, are often hard to find, due to busy schedules and lack of familiarity with bibliometric studies.
- Users of the bibliometric maps (policy makers for example) are often too much overwhelmed by the amount of information in the maps. Often, policy makers have a hard

time in understanding what kind of information the maps show, and then conclude that they know too little of the field in order to be able to extract relevant information.

Two important assumptions play a central role in the development of bibliometric relational indicators:
The first assumption is that cognitive, institutional and social interaction patterns in the research system can be measured through the analysis of publications. In other words, we assume that bibliographic information may represent the actual structure and dynamics in research.

The second assumption is, that bibliometric mapping may provide physical representations of interrelations between (or within) fields, disciplines, researchers, institutions, countries. In these maps the relative locations of entitities are depicted. The distance between the locations of entities in the map is analogous with the degree of simularities between the depicted entitites. Alternatively, maps of science can be visualisations of network structures in research. In visualisations of network structures, the principal information is not topological (that is location and distance), but relational. This relational information is represented in graphs showing connection patterns and the strength of the links between the entities represented in the network graph. (see Callon M., J. Law, A. Rip, 1986).

The construction of relational indicators is based on a set of relatively advanced statistical methods and techniques. This set of methods is generically defined as Multivariate Data Analysis. The general aim of Multivariate Data Analysis methods is to provide a simultaneous representation of relations between multiple variables. Multivariate Data Analysis methods are especially apt to present information of the underlying structure, or on specific regularities or patterns, of simultaneous relationships among three or more variable which are interelated with each other (for a nice overview of applications of Multivariate Data Analysis in bibliometrics see Tijssen R.J.W., J. de Leeuw, 1988). Of all the Multivariate Data Analysis methods the most significant for the costruction of bibliometric relational indicators are: Multidimensional Scaling (MDS) (see Egge L., R. Rousseau, 1990, pp. 105-112), Cluster Analysis - a subclass of which is the Network Analysis (see Egge L., R. Rousseau, 1990, pp. 112-124) and Correspondance Analysis (see Ludovic L et al., 1984).

5.2 Types of bibliometric relational indicators and techniques

M. Callon, (1993, p. 57), differentiates between two generations of bibliometric relational indicators. The main difference between first and second generation is that the first generation of relational indicators is based mainly on bibliographic (including citations) information, while the second generation is based on the analysis of the text in the scientific publications.

In the first generation of relational indicators, Michel Callon classifies the following indicators (methods):

1. Indicators measuring and depicting collaboration patterns in research (based on co-authorship data);
2. Indicators measuring interactions between science and technology (based on 'patent to scientific literature citation'-data);
3. Graphs of citation networks and co-citation analysis.

In the second generation of relational indicators M. Callon classifies all the indicators, mapping methods and techniques based on co-word analysis (Callon M., 1993, pp 77-100). Both citation networks, co-citation analysis and co-word analysis aim to measure and depict the structure and the dynamics of the content of research. Citation networks and co-citation analysis build on information about citation patterns. Co-word analysis makes use of content related bibliometric information (such as key words, words in the title, abstract or the main text of the selected set of publications).

In the following we shall briefly introduce to the four types of relational indicators mentioned above. However, the reader should bear in mind, that there is a great variety of analytical concepts, methods and techniques within each one of the above mentioned types of relational indicators. It is, therefore, difficult to give a succinct account of this multitude of methods.

5.3 Measuring collaboration patterns

A co-authorship is the result of collaboration between researchers taking part in a particular joint research effort. Therefore, co-authorships are traces of collaborative links between individuals, but also between organisations (co-occurrence of institutional affiliations in a

publication) or countries (co-occurrence of institutional addresses from different countries in a publication). There are three main types of bibliometric indicators measuring collaboration patterns:

1. Counting the number of co-authorship pair-links identified in a set of publications: This is the basic bibliometric indicator for measuring collaboration in research. This indicator is scalar.

2. Affinity index: This indicator measures the relative rate of research collaboration between two countries and in relation to all international co-operation of these two countries.
Affintity index for the country X is defined as:

AFI = The number of co-authorship links between country X and Y divided by the number of collaboration links between the country X and the world.

The values of AFI are always within the interval (0,1). According to Ocubo Y., 1997, this indicator measures not only the links between countries, but also the equilibrium level of the collaboration between countries (for a critique against the use of this indicator see Luukkonen T. et al., 1993, pp. 19-22.) With a slight modification AFI can be applied to entities other than countries (universities for example).

3. Co-authorship matrix: For more advanced studies of collaboration patterns and research networks, it is possible to construct an 'n x n' co-authorship matrix, where n is the number of collaborating units (authors for example) and in each cell of the matrix is counted the number of co-authorship links. This matrix is subjected to cluster analysis or network analysis for revealing the underlying collaboration clusters (for more details about technical aspects of depicting research networks, see Luukkonen T. et al., 1993).

These three types of indicators have been used in various studies to:

- Measure and analyze international collaboration activities in research (European Commission, 1997, pp. 663-667).
- Measure and analyse collaboration between countries (Luukkonen T. et al., 1993)
- Measure and analyse collaboration between industry, public research institutions and universities in a national system (Kaloudis A., 1995)

- Measure and analyse corporate collaboration networks (Hicks D. et al., 1996)
- Measure and analyse collaboration between universities (Persson O. et al., 1997)
- Measure and analyse collaboration patterns in a research field (Meyer M., O.Persson, 1998)
- Study research network dynamics (Luukkonen T., et al., 1993).

Limitations of co-authorship indicators as a measure of collaboration in research

It is obvious that not all research collaborations lead to co-authored papers. In addition, we do not know whether all researchers in the list of (co)-authors really contributed to the production of the article. Thus, when we infer from co-authorships to collaborations we are running the risk of neglecting some collaborations as well as being insecure about the actual reasons behind co-authorship. Consequently, one should use co-authorship data as a rough indicator of collaboration, especially at meso- and micro level of analysis (for further discussion on this issue see Melin G., O. Persson, 1996).

5.4 Measuring knowledge flows between science and technology

The basic indicators of knowledge flows from science to technology are:

- Citations to scientific publications in patents.
- Length of time between the publication of scientific articles and patent applications.

Citations to scientific publications in patents

Citations to scientific publications in patents are the most used indicator for measuring knowledge flows from science to technology. Both citations by inventors and citations by examiners are relevant information.

The basic assumption underlying the use of this indicator is that technology output is represented in patents while science output is represented in the scientific literature. Thus, citations to scientific papers in patents must represent the use of science (methods, ideas, processes) in technology.

The number of citations from patents to scientific literature give an indication which technological sectors are science-based and which are not. The type of the cited scientific

literature (basic, applied, field specific etc.) provides an indication of which scientific areas are important for a given technological sector.

In general, this indicator has been used to analyse:

- the extent to which patent applicants and examiners utilise research findings
- the nature of the cited research activity (whether the citations are to basic or applied research, to a narrow or wide range of scientific fields, to old or new papers).
- the performers of the cited scientific literature

Length of time between the publication of scientific articles and patent applications

The parallel development of publications and patents can be considered a strong indication for a close interaction between science and technology. Measuring the length of time in which an issue appears from the scientific publications to patents may provide an indication of structural aspects of knowledge diffusion in this particular field. This may be a key-information for research policy makers. However, measuring this indicator is not an easy task, methodologically speaking. For a more detailed discussion on these two indicators, see Schmoch U., 1993, and Carpenter M. P., 1980.

5.5 Measuring the structure and the dynamics of research

There are basically three methods to measure and analyse the structure and the dynamics of science: co-citation analysis and co-word analysis.

Citation networks

Citations may be used to study questions such as: To what extent are the research system of a country integrated into the international network of science?; Or what is the pattern of knowledge flows from one research field to another? Or what are the important cognitive contributions in a field? Or how researchers in a field are connected by citing the one the other ('invisible college')?

The main idea here is to construct a directed citation matrices, which can be used for the visualisation of citation networks (for more details see the seminal paper of Derek de Solla Price, 1965 and Persson O., M. Beckmann, 1995)

Co-citation analysis

Two documents are said to be co-cited when they both appear in the reference list of a third document. Co-citation analysis is the analysis of co-citation patterns. The main assumption behind co-citation analysis is that if many papers co-cite the same pair(s) of papers in their reference lists, then there is a high degree of referencing consensus, and thus, a cognitive connection between this pair(s) of papers. Because of this observed referencing consensus, co-citations provide a way to map the relationships between key ideas in a research field. This can be done by classifying and grouping (clustering) the selected set of papers by their common referencing to clusters of highly cited and highly co-cited previous papers. This highly cited and highly co-cited reference papers are called 'core papers'. It is the reference papers citing the 'core papers' that are actually clustered. The assumption, now is that these 'core papers' represent the 'intellectual base', that is, the cores of theories and methods around which the current research is organised (see for example Griffith B.C. and H. Small, 1974).

A co-citation bibliometric map is a detailed representation of the structure and content of co-citation clusters based on the strongly shared citing patterns among the current scientific literature. These co-citation clusters have been shown, on the basis of validation studies with experts, to represent actual thematic research units on which science is composed at the cognitive level (for more details see Franklin J.J. and Johnston R., 1988).

One of the advantages of this method is that through the network of co-citation clusters, it is possible to identify intellectual bridges between different scientific domains.

Co-word analysis

A different approach to co-citations for the analysis of field structures and the identification of core areas of research is that of co-word analysis. Co-word analysis is a method to identify thematic networks (or interrelated clusters of research topics) based on the co-occurrence of key-words in a selected set of publications.

The main assumption behind this method is that if two non-trivial words (for example scientific terms) appear (occur) at the same text this is an indication that they are thematically related. The more frequent two key-words occur together the stronger the possibility that these two words are thematically interconnected.

The analytical process follows four steps. First, the texts of the selected publications are transformed into strings of key-words, or key-words are selected by experts in the field. Second, all the key words are aggregated in a list. Third, the co-occurrences of the identified key-words in the text of the selected papers are counted and the co-occurrence matrix (that is an n x n matrix, where n is the number of the identified key-words) is calculated. Fourth, the co-occurence matric is subjected to cluster analysis from which we receive a network of key-words. The assumption is that this network of key-words reflects real thematic interrelations between research topics. (for more details see Callon M., J. Law, A. Rip, 1986). The theroretical foundation of co-word analysis has been further developed and expanded in Leydersdorff L., 1995.

Both co-citation and co-word analysis can be applied to:

- Identify the international structure of research fields
- Identify 'weak' points in national research systems compared to international trends.
- Identify rapid changes in a given speciality or sub-field.

5.6 Advanced visual representations of scientific fields

In the last years, the visual representation techniques of scientific fields have developed enormously, both technically and methodologically. We discuss here two of the most promising examples of such representation techniques. The one is ISI's virtual reality software based on citation analysis methodologies. The other is developed at the Centre of Science and Technology Studies (CWTS) and is based on advanced co-word methods.

Visual representation techniques based on citation analysis techniques:

The idea with ISI's virtual reality software is to provide a tool with which it will be possible to navigate in a structured SCI database (this is called a global mapping approach). Some new ideas and methods have been applied to improve the short-comings of co-citation analysis. A detailed description of this new methodology is presented in Small H., 1997.

Visual representation techniques based on co-word analysis

A different approach to visual representation techniques is the one developed at the Centre of Science and Technology Studies (CWTS) by Ed M. Noyons and A.J.F. van Raan (see also at http://sahara.fsw.leidenuniv.nl/cwts/cwtshome.html).

This approach focuses on the present activities in a field and not on the past activities In co-citation analysis the structure of a field is generated by identifying high impact co-cited documents (the classics, or the core contributions in the field). These documents constitute the 'intellectual base' of a set of current documents.

Noyons E.M., A.J.F. van Raan, start the contruction of their maps from the opposite assumption, namely, it is not the history (the highly co-cited past documents) but the present (the scientific content of the recent documents) which reflects the direction of the frontiers of knowledge in a research field. They use set of recent publication to identify what is the recent structure of the field and how the field has been evolved to this recent structure. Their methodology is simple in principle, but advanced technically.

The fist step in their analysis is to select a set of journals publishing work in the field under study. The second step is to identify candidates for the core topics in a field by counting the most frequent noun phrases in the titles of recent publications (usually publications of the last two years). That is, one identifies the most frequent word combinations in the set of the selected publications. These noun phrases are extracted from the titles (or abstracts) of publications by a linguistic software.

The third step is to subject the top list of the most frequent noun phrases to a co-word analysis. This means, that the co-occurrences of each noun-phrase with any other noun-phrase in the list are calculated. Each time two noun-phrases co-occur in the same title or abstract, a co-occurrence is counted. Thus, the titles and the abstracts of the selected set of publications decide which noun-phrase in the selected list of the most frequent noun phrase are related to each other. This leads to an 'n x n' matrix of co-occuring noun phrases where 'n' is the number of the identified core noun phrases.

The fourth step is to subject this co-occurrence matrix to a clustering analysis. The clustering algorithm identifies the number of noun phrase-clusters. It is assumed that these noun-clusters represent thematic sub-domains within the field. Consequently, publications are assigned to a thematic sub-domain on the basis of the noun-phrases they have in their title or abstract.

The final step of this methodology is to 'super-impose' the revealed recent structure of the filed over the publication data from preceeding periods, In this way, it is possible to investigate how the structure of a field has evolved to the 'present' situation. These series of maps constitute a dynamic map (a film of maps).

In order to find out more about characteristics of each of the identified sub-domains, it is possible to list the most frequently cited references, the most active actors (authors, organisations, institutes) or the top list of cited institutions.

Also other bibliometric groups (see for example Katz J.S., D. Hicks, 1997) have or are in the process of developing softwares and techniques for advanced bibliometric analysis targeted to research policy analysis. Visual representations of this kind, are a powerful and tool for research policy makers, but also for 'research intelligence' purposes.

5. 7 Methodological considerations

As decision support tool, maps of science, may be a powerful policy instrument. New complex interactions and structures in research develop continually challenging research policy activities. Relational indicators and in particular maps of science reduce this complexity and, thus, render the research landscape more managable.

But there are some serious methodological limitations related to the construction and interpretation of these indicators. First, there are a series of general assumptions (about the meaning of co-authorships, citations, co-citations, co-word etc.) behind each one of the relational indicators which one can question their validity. This creates some doubts about what the maps actually represent. Bibliometric maps are not representations of research fields 'as such', but they are constructions in their own right. As Arie Rip, 1988 puts it: 'Their (maps) link with the ongoing science, and their value, consist in the way they relate to (building blocks of) scientists' accounts, and in the aggregation of data that occurs and creates a view of outcomes of scientific accounts at the collective level (my italics)'.

Second, there are some unsettled technical issues concerning the stability, the statistical properties and the thresholds used in the most of the cartographical representations of

research. There is a need for understanding better the mathematical and statistical properties of relational indicators.

Despite all these methodological considerations, one cannot ignore the potential of the new generation of advanced visual techniques and methodological developments of the last 5 years.

5.8 Relational indicators: to conclude

Bibliometric relational indicators have been developed by the last 10-20 years to map cognitive, social and institutional research interactions and knowledge flows in science. We presented three types of indicators:

1. Indicators measuring and depicting collaboration patterns in research (based on co-authorship data).
2. Indicators measuring interactions between science and technology (based on 'patent to scientific literature citation'-data).
3. Indicators and cartographical representations of the strucutre and dynamics of research fields based on networks of citations, co-citation analysis and co-word analysis.

The new bibliometric mapping devices introduce us to a new generation of instruments for research policy, research strategy and 'research intelligence'.

6. Conclusions

Research policy makers are in need of more reliable and accurate tools for monitoring, evaluating and exploring aspects of modern research systems. It is particularly important to further develop existent methods and techniques of monitoring the cognitive and the institutional aspects of research dynamics. The general societal orientation towards 'knowledge economies', 'innovation systems', and 'R&D intensive global industries' necessities this. Bibliometric performance and relational indicators may provide vital information for the formulation of research strategies at the macro- (national) and meso- (institutional) levels.

In section 2 of this Chapter we tried to introduce to some of the most basic concepts and assumptions underlying bibliometric statistics and bibliometric analysis. Section 3 introduces to the most common bibliometric datasources, particularly to Science Citation Index, and to their limitations.

An overview of the basic bibliometric indicators for studying research performance issues has been presented in section 4. The most important lesson from this brief presentation is that none indicator of this kind is self-sufficient. These indicators has to be used in combination (activity, impact, expected impact, etc.) in order to create institutional (or national) research profiles. These profiles are a valuable source of information for an intelligent research policy.

In section 5 we presented basic relational indicators for measuring interactions, structure and dynamics in research. It is clear that these indicators are a powerful tool for monitoring and exploring possibilities for strategic interventions in the rapid changing R&D landscapes. A number of assumptions underlying the interpretation of bibliometric 'maps of science' has to undergo further quantitative and qualitative validation and control. Use of these maps in a policy context, takes place only in a close collaboration with experts of the fields.

The irony is, that the more sophisticated methods and techniques are developing in bibliometrics, the more bibliometricians are in need to come closer and to develop sophisticate communication channels with researchers, experts on their field, and policy makers. This is in a sharp contrast with the belief that bibliometrics has to be an observatory of the 'written science' independent of scientists. Creating links with other 'research on research policy' traditions - especially those which are more oriented towards qualitative studies - and balancing the complex communication dynamics with the community of researchers and policy makers is the main challenge of the future (see also Leydersdorff L., 1995).

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VI. RESEARCH DATABASES

Pari Patel, Rajsneesh Narula & Finn Ørstavik and Svein Olav Nås

This chapter describes three datasets developed by researchers in various institutions; these datasets use different methodologies and different data sources. Each was developed for the purpose of answering specific research questions. But databases such as these often point the way towards new indicator developments and applications, and each of the databases described here also supports research projects of policy relevance. The databases which we look at there are:

- The SPRU large-Firms Database
- The MERIT-CATI database on technology co-operation agreements and alliances
- The NIS-2 database on inter-firm technological collaboration

In each case, we describe how the database was constructed, the types of results which have been achieved using it, and its strengths and weaknesses.

1. THE SPRU LARGE FIRM DATABASE

Underlying Rationale

The underlying rationale for constructing the database is that firms have a central role in innovative activities as the key institutions involved in bringing new technology to market. A major reason for focusing on the activities of large firms is that despite the rhetoric on the importance of small firms, large firms are a major source of new technology and innovation, especially in the so called 'high technology' sectors (Chemicals and Electronics). Further, case studies have shown that large firms also contribute to the development of technology (and new products) in other smaller firms such as the suppliers of their production equipment, components and software. Thus strategic decisions by these firms can have a major impact on the sectoral patterns of technological activities, and competitive performance, of whole countries and industrial sectors. However despite their importance very little firm-specific data is

available over time and in detailed fields of technology. The main aim in constructing the SPRU Large Firms database was to provide such information.

Population of Firms

The database population is made up of the world's largest firms according to sales drawn from the Fortune 'Global 500'[1] in the 1980's and the 1990's . From the Fortune list SPRU have excluded firms which are not technologically active in patenting in the USA. Thus the database contains over 500 firms with information on sales, employment, principal sector of activity, country of origin (i.e., country of headquarters), R&D expenditures, derived from Fortune and other sources such as Company Reporting and Disclosure. To this SPRU have added data on the US patents granted to each firm since 1969 obtained from the US Patent Office. For a number of companies the country of origin is not immediately obvious and SPRU have made the following arbitrary decisions for this report: ABB is regarded as Swiss, Smithkline Beecham, Unilever and Hanson as British, and Shell as Dutch.

Treatment of the Patent Data

The database contains the following information for each patent:

- The technical field. SPRU have developed and used 2 different levels of classification - 91 detailed fields and 34 broad fields, depending on the purpose of the analysis. The former is based directly on the US patent classification and the latter is based on an aggregate of the 91 classes.
- The country of residence of the inventor. This is not necessarily the country from which their patent application was filed, and is a more accurate reflection of the country in which the technological activity was performed.

The main difficulty in using the primary data at the company level is that many patents are granted under the names of subsidiaries and divisions that are different from those of the parent companies, and are therefore listed separately. In addition the names of companies and other institutions are not unified, in the sense that the same

[1]Published near the end of July of each year.

company (or institution) may appear several times in the data, with a slightly different name in each case. In the latest version of the database firms have been consolidated on the basis of Who Owns Whom for 1992 and unified all the names for the period 1980-96. This process has enabled us to identify some 4000 different assignee names for 359 firms. Previous consolidations were based on Who Owns Whom for 1984 and 1988.

Advantages and Limitations of the Patent Data

Patent statistics have been used frequently by economists and other analysts as a proxy measure of technological activities. Since a patent is granted normally in recognition of technical novelty, these data are better able to capture technology creation than technology diffusion-transfer-imitation. For those who assume that technology is information (i.e costly to create, but virtually costless to transfer and reproduce), this distinction is a rigid one. However, in the real world of technology that is complex, partially tacit and specific, the diffusion-transfer- imitation of technology generally requires technological activities by the imitator, which sometimes result in improvements over the original. Patenting activities do reflect this type of imitation, which is typical of advanced country companies competing close to the world's technological frontier. However, they do not reflect many other types of imitation and related technological activities not involving originality, such as trade in capital goods and know-how, on-the-job training, assimilative R & D and production engineering, and the foreign education of scientists and engineers.

The general advantages of the patent data compared to other measures, such as R & D expenditures, are that - with the advent of modern information technology - they are readily available over long time periods; they can be broken down in great statistical detail, technical field and geographical location; and they capture technological activities undertaken outside R & D departments, such as design activities in small firms, and production engineering in large firms. Their main general disadvantage is that, like other routine measures of technological activities, they do not measure satisfactorily one of the major fields of technological growth, namely, software.

Main Uses of the data: Measuring and Mapping Technological Competencies

The basic premise of the research concerned with mapping and measuring firm-specific technological competencies is that they are major factors in explaining why firms are different, how they change over time, and whether or not they are capable of remaining competitive. The above database allows us to analyse two elements of firm-level technological competencies: their spread across different fields of technology (or technology diversification) and their spread across different geographic locations (or internationalisation of technology).

Multi-Technology Large Firms

The main research (Granstrand et. al. (1997), Patel and Pavitt (1997)) on 440 firms across 16 principal product groups and with their patenting activities broken down into 34 technical fields, shows that technological competencies have the following characteristics:

1. They are typically multi-field with substantial proportion of activities outside what would appear to be the core fields. For example:

Table 6.1. Firm activities outside core-fields

Electronics firms	= ~34% outside broad elect./electronic fields,	of which ~ 20% in machinery;
Chemical firms	= ~33% outside broad chemical fields,	of which ~ 16% in machinery;
Automobile firms	= ~70% outside broad transport fields,	of which ~ 46% in machinery.

Thus firms in all sectors are active in machinery technologies, where they often do not have a distinctive technological advantage, and where smaller firms are particularly active.

2. The range of technological competencies is broader than the range of products as shown in Table 6.2, which compares the number of firms with their principal activity in selected product groups with the number of firms active in their corresponding distinctive technologies. In all cases, the latter is considerably larger than the former.

3. Thus each firm has a measurable profile of competencies, with varying levels of commitment and competitive advantage in a range of technological fields. In

general, firms' technological profiles are highly stable over time, reflecting the localised and cumulative nature of technological learning. Fewer than 10% of the 440 firms have no significant correlation between their profiles in 1969-74 and in 1985-90.

Table 6.2. Number of Active Large Firm's in Selected Principal Products, and in closely related Technologies, 1985-90.

Principal Product	No. of Firms (out of 440)	Technological Field (out of 34)	No. of Active* Firms (out of 440)
Computers.	17	Calculators & Computers, etc.	151
Electrical & Electronic	56	Semiconductors.	94
Instruments.	21	Instruments and Controls.	288
Chemicals	66	Organic Chemicals.	190
Pharmaceuticals	25	Drugs and Bioengineering.	114
Mining and Petroleum	31	Chemical Processes.	304
		Apparatus for chemical, food, etc.	234
Non-Electrical machinery	58	Gen. Non-elect. Industrial equip..	246
		Non-elect. specialised ind. equip.	241
		Metallurgical & metal working equ.	225
Automobiles	35	Road vehicles & engines	77
Aerospace	18	Aircraft	28

* With five or more patents granted 1985-90.

4. The technological fields where firms have been acquiring an in-house capability most vigorously since the early 1970s - computers, biotechnology and pharmaceuticals, and materials - are also those where firms have increased most vigorously their external alliances for technological exchanges and joint developments.

5. Large firms' technological profiles are highly differentiated, according to the products that they make. Firstly firms have significantly different profiles of technological competence to most others: only 15% (of the 440 firms) are similar. Secondly, in all sectors firms have a higher probability of finding others with similar technological profiles within their sector than outside their sector: from twice as high for machinery firms, to more than ten times as high for pharmaceutical firms. Thirdly, the frequency of technological proximity between firms in different industrial sectors is not evenly spread or random, but reveals 3 distinct groupings:

* chemicals, pharmaceuticals, and mining and petroleum sectors;

* machinery and vehicles

* electrical and computers.

These results:

- ➨ Confirm the importance of path dependency in the accumulation of firm-specific technological competencies.
- ➨ Confirm the importance in technology strategy of integration (or "fusion") of different fields of technological competence.
- ➨ Challenge much of the current conventional wisdom about technology strategies in large firms. In particular, they show the following:

* Large firms are heavily constrained in their choices about technology strategy.

* External alliances in technology are a complement to internal competence-building, and not a substitute for it. In technology strategy, "make or buy" is not a feasible choice set.

* Radical technological breakthroughs are very unlikely to destroy all - or even the majority - of technological competencies in large firms. Indeed, they are more likely to augment the range of competencies that firms develop.

* In many sectors (particularly transportation) large firms do not focus their technological activities only on their "distinctive core competence", but also on technological linkages in their supply chain.

* Notions of "focus", normally applied to production and marketing strategy, do not necessarily apply to technology strategy.

Geographic Spread of Technological Competencies Within Firms

SPRU have also examined the nature and extent of the geographic spread of technological activities within large firms using the database[2] (Patel & Pavitt (1991), Patel (1995, 1996) and Patel and Vega (1997, 1998)). The main 'stylized facts' to emerge from comparisons of more than 500 large firms based in Europe, Japan and the US for the period 1980 to 1996 are as follows:

[2] Using the the country of residence of the inventor of a patent as a proxy measure for where the technological activity was performed.

1. Large firms continue to perform a high proportion of their technological activities in their home[3] countries although there are some differences amongst them, mainly according to nationalities, with Japanese firms continuing to concentrate their activities in Japan and European firms locating more technology outside their home countries.

2. Within Europe, the share of corporate technological activities performed outside their home country is higher in those from small countries (more than 50% in firms from Belgium, Netherlands and Switzerland) than in those from large countries (a third or less in firms from France, Germany and Italy). The main exceptions are large British firms with more than 50% outside the UK.

3. The geographic spread of foreign activities of these firms is uneven with the USA, Germany and the UK accounting for the largest proportion and Japan very little.

4. The proportion of firms' technological activities performed abroad decreases with the technology intensity of the industry and the firm (Patel (1995 and 1996)). Thus the industries with the most internationalised firms are food and drink, building materials, and mining & petroleum, and the least internationalised are aircraft, instruments and automobiles.

5. Analysing the activities of the most internationalised large firms, Patel and Vega (1997) show that in a large majority of cases these firms tend to locate their technology abroad in their core areas where they are strong at home and where the location has complementary strengths. In a small minority of cases, firms go abroad in their areas of weakness at home to exploit the technological advantage of the host country.

These results suggest that adapting products and processes and materials to suit foreign markets and providing technical support to off-shore manufacturing plants is a major factor in the internationalisation of corporate technology. They are also consistent with the notion that firms are increasingly engaging in small scale activities

[3] Country in which their headquarters is located.

to monitor and scan new technological developments in centres of excellence in foreign countries within their areas of existing strength. However there is very little evidence to suggest that firms routinely go abroad to compensate for their weakness at home.

2. THE MERIT COOPERATIVE AGREEMENTS AND TECHNOLOGY INDICATORS (CATI) INFORMATION SYSTEM

The MERIT-CATI database was developed in the late 1980s at the Maastricht Economic Research Institute on Innovation and Technology (MERIT) at the University of Maastricht, the Netherlands. Professor John Hagedoorn has been the primary researcher responsible for this database since its inception. Its focus remains mainly on the issue of cooperative agreements, but with the assistance of several other of his colleagues at MERIT, the dataset has evolved over the years to include other issues tangential to the original project, including mergers and acquisitions and globalisation. The issue of cooperative agreements is a broad one, and it has thus been necessary for CATI to be increasingly specialised: Its focus has been narrowed so as to concentrate on strategic technology partnering, or cooperative agreements that are strategic in nature and involve some level of innovative activity. Further, there has been a implicit attempt to focus on new 'core' technologies: information technology, new materials and biotechnology, although there is considerable information on other industries. Because it has been updated on a yearly basis since 1988, it represents the single largest database on strategic technology partnering in existence anywhere, since the data is available on a comparable basis for a 15 year period from 1980 to 1995, and is updated annually.

What are cooperative agreements?

There is some confusion about the meanings of collaborative/cooperative agreements, networks and strategic alliances, with these terms often being used as synonyms. Cooperative agreements include all inter-firm collaborative activity, while strategic alliances and networks represent two different (though related) subsets of inter-firm cooperation.

More specifically strategic alliances refer to inter-firm cooperative agreements which are intended to affect the long-term product-market positioning of at least one

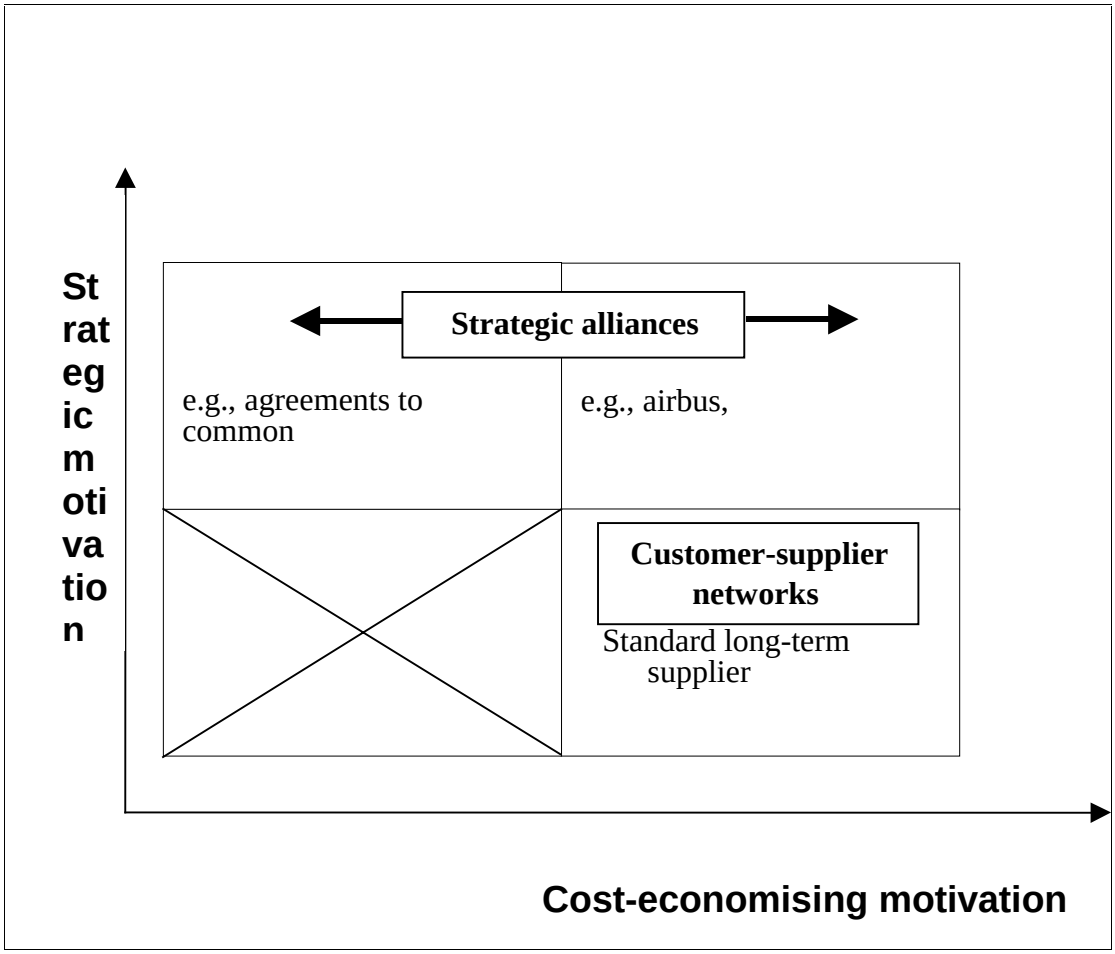
partner[4]. The CATI database focuses primarily on alliances where innovative activity is at least part of the agreement, which are referred to as either strategic technology partnering (STP) or strategic technology alliances. What differentiates a strategic alliance from a customer-supplier network is the underlying motive of the cooperation (Figure 6.1). The literature suggests that most cooperative agreements have two possible motivations[5].

First, there is a cost economising motivation, whereby at least one firm within the relationship has entered the relationship to minimise its net costs, or in other words, it is cost-economising. Agreements which are mainly aimed at doing this are generally (but not always) customer-supplier agreements, or vertical relationships within a value-added chain and embody a shorter-term perspective.

Figure 6.1 Explaining the underlying differences between strategic alliances and customer-supplier networks

[4] See J. Hagedoorn (1993b)

[5] Considerable recent debate has centred around these seemingly alternate schools of thought. Recent work has attempted to show their complementarity. For a succinct overview, see Anoop Madhok, Cost, value and foreign market entry mode: the transaction and the firm, Strategic Management Journal, Vol. 18, pp 39-61, 1997

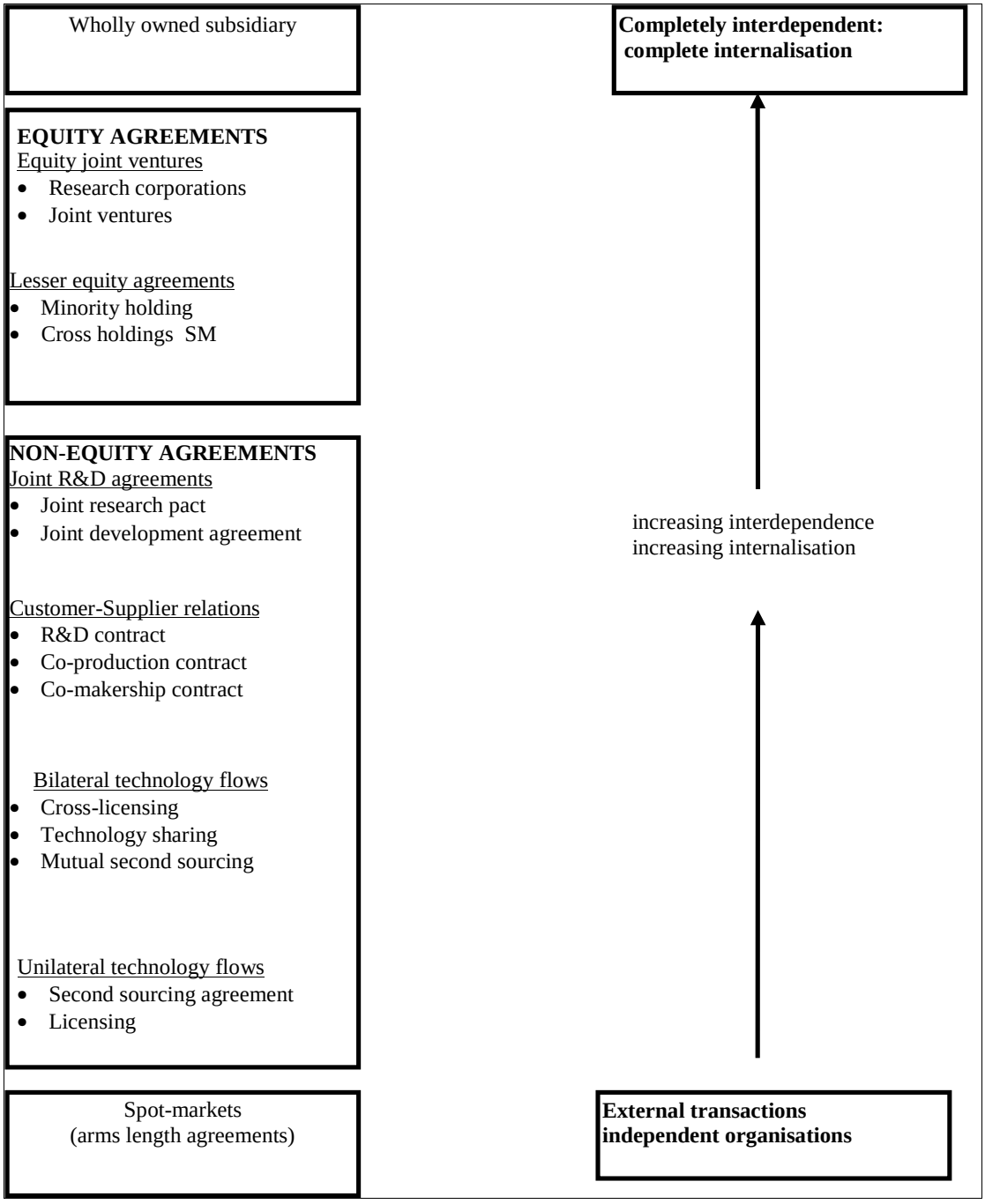


Source. Narula and Hagedoorn (1998)

Secondly, firms may have a strategic motivation. Such agreements are aimed at long-term profit optimising objectives by attempting to enhance the value of the firm's assets. It important to understand the distinction being made here. While cost-economising actions, such as acquiring a minority share in a supplier, may increase profits, it is often not the case that the value of the firm is enhanced beyond the short-term (e.g., the hundreds of cost-cutting, outsourcing agreements that each major company has). When a firm engages in an agreement that, say, develops a common standard with a rival (e.g., Sony and Philips to establish DVD technology standards), it is often forgoing a much higher short-term profit (were it to go it alone) in the hope that the joint standard will enhance it long term market position. Of course, firms would like to do both at the same time: increase short term profits through cost-economising as well as long-term profit maximise through value enhancement, but this is not always possible. It is important to emphasise that very few agreements are distinctly driven by one motivation or the other. What we are trying to establish here is that agreements that are established with primarily short-term cost efficiencies in

mind are generally customer-supplier networks, while agreements where a long-term value enhancement is the primary objective are strategic alliances. Figure 6.1. (above) illustrates the basic argument with a few examples.

Figure 6.2 Organisational modes of inter-firm cooperation and extent of internalisation and interdependence



Source. Narula and Hagedoorn (1998)

What kinds of agreements are classified as strategic technology partnering? Figure 6.2. describes the range of inter-firm organisational modes generally utilised in collaborative agreement activity: There are a wide range of types of agreements, reflecting various degrees of inter-organisational interdependency and levels of internalisation. These range from wholly-owned subsidiaries, which represent completely interdependency between the firms and full internalisation. At the other extreme, lie spot-market transactions, which totally independent firms engage in arms-length transactions in which either firm remains completely independent of the other. As Figure 2 illustrates, CATI includes within the rubric of collaborative agreements two broad groupings of agreements which can be regarded as representing different extents of internalisation. Although it is difficult to be specific and concrete regarding the ordinal ranking, it is safe to say that equity-based agreements represent a higher level of internalisation and inter-organisational interdependence than non-equity agreements.

Description of the database

Although additional data on mergers and acquisitions, patenting by individual firms, and other firm-level indicators of technological competitiveness have been added, the core of CATI rests on cooperative agreements. Its biggest strength is that it provides data on an important subset of cooperative agreements, that of strategic technology partnering, and that this data is available on a comparable basis for a 15 year time series between 1980 and 1995. Other sources of data are either available for a shorter time period, most often for a single year, and cover the more general spectrum of alliances. However, it has two big weaknesses. First, it is based almost exclusively on secondary data sources. Data are gathered from newspapers, trade journals and other external sources. As such, only announced agreements are included, which does not necessarily imply that these alliances occur, and his also means that alliances that have not been announced in the press are not recorded. Furthermore, there is a bias towards English-language press announcements, thereby giving the database an Anglo-Saxon bias. Second, no information is compiled regarding the outcome (or lack thereof) of the alliance. This, however, is much more difficult to establish, since firms involved in technology alliances are reluctant to share such information with

researchers, nor are motivated to reveal their true intentions, expectations and benefits from an alliance, since it may provide a competitive edge to their competitors.

Only those inter-firm agreements are collected that contain some arrangements for transferring technology or joint research are included in CATI. Joint research pacts, second-sourcing and licensing agreements are clear-cut examples. We also collect information on joint ventures in which new technology is received from at least one of the partners, or joint ventures having some R&D program. Mere production or marketing joint ventures are excluded. The analysis is primarily related to technology cooperation. And within this group, attention is focused on only those forms of cooperation and agreements for which a combined innovative activity or an exchange of technology is at least part of the agreement. Consequently, partnerships are omitted that regulate no more than the sharing of production facilities, the setting of standards, collusive behaviour in price-setting and raising entry barriers - although all of these may be side effects of inter-firm cooperation as defined by CATI.

Information is available for each alliance includes: the number of companies involved; names of companies (or important subsidiaries); year of establishment, time-horizon, duration and year of dissolution; capital investments and involvement of banks and research institutes or universities; field(s) of technology[6]; modes of cooperation[7]; and some comment or available information about progress. Depending on the very form of cooperation the MERIT –CATI group has collected information on the operational context; the name of the agreement or project; equity sharing; the direction of capital or technology flows; the degree of participation in case of minority holdings; some information about motives underlying the alliance; the character of cooperation, such as basic research, applied research, or product development possibly associated with production and/or marketing arrangements. In addition, for three separate subsets of firms time-series for employment, turnover, net

[6] The most important fields in terms of frequency are information technology (computers, industrial automation, telecommunications, software, microelectronics), biotechnology (with fields such as pharmaceuticals and agro-biotechnology), new materials technology, chemicals, automotive, defence, consumer electronics, heavy electrical equipment, food & beverages, etc. All fields have important subfields.

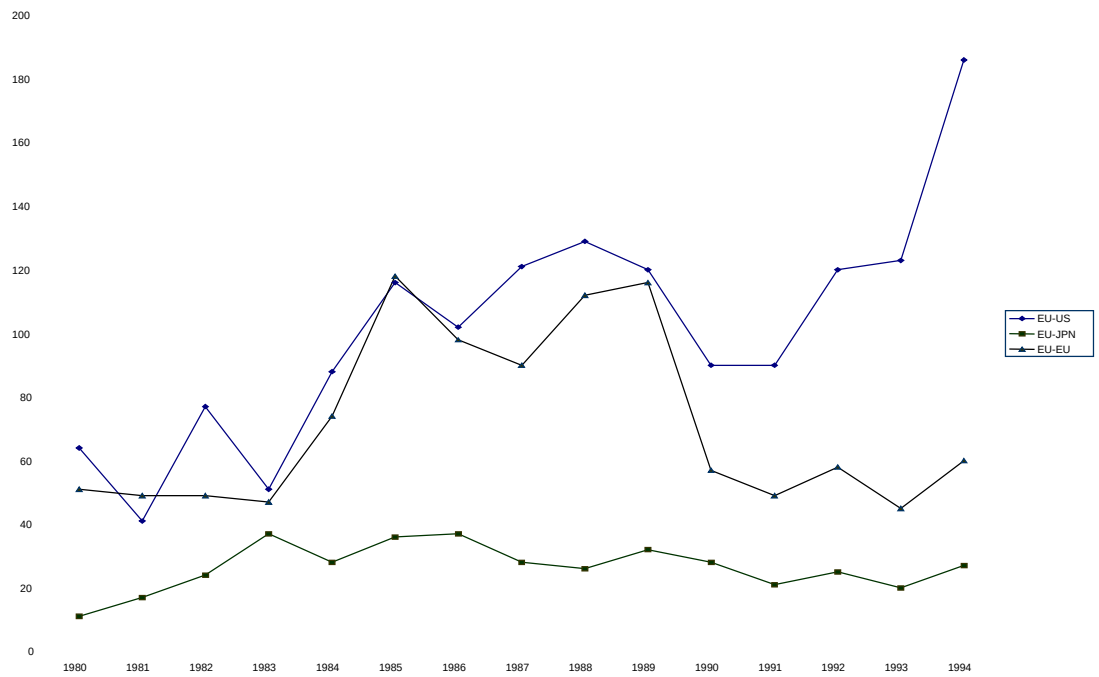
[7] As principal modes of cooperation we regard equity joint ventures, joint R&D projects, technology exchange agreements, minority and cross-holdings, particular customer-supplier relations, one-directional technology flows. Each mode of cooperation has a number of particular categories.

income, R&D expenditures and numbers of assigned US patents have been stored. The first subset is based on the Business Week R&D scoreboard, the second on Fortune's International 500, and the third group was retrieved from the US Department of Commerce's patent tapes. From the Business Week R&D Scoreboard we took R&D expenditure, net income, sales and number of employees. In 1980 some 750 companies were filed; during the next years this number gradually increased up to 900 companies in 1988, which were spread among 40 industry groups. The Fortune's International 500 of the largest corporations outside the US provides amongst others information about sales (upon which the rankings are based), net income and number of employees.

Main research areas and primary findings

Overall trends

Figure 6.3: Number of new STP per year by EU fimrs, 1980-94



Source: Narula (1998)

Overall trends in STP activity suggests that the general growth pattern of newly made strategic alliances has been phenomenal since 1980 (Figure 6.3). The data indicate

that the number of strategic technology partnering agreements have been increasing over time. However, since the mid-eighties there has been a certain degree of differentiation in growth patterns. The growth pattern of newly established alliances between companies from Japan and the EU has more or less stabilised. After a steady increase of newly made non-domestic alliances within the EU during the first half of the eighties, there appears to be a gradual stagnation in the growth of these intra-regional (non-domestic) alliances within the EU towards the end of the period. To some extent this pattern, though at a higher overall growth level, is also visible for the increase of the number of alliances made between firms from the US and Japan. Although there are fluctuations in the growth of international alliances between companies from the US and the EU, the data suggests an overall rise for newly established partnerships throughout the period, after some decrease in the growth of newly made alliances at the end of the eighties. Further study of the CATI data reveals that this increase in US-EU alliances is in particular due to the growth of contractual alliances of which the number in recent years is several times that of the number of equity partnerships.

It would be reasonable to expect that with the fall in the cost of cross-border transactions between EU countries because of integration, intra-EU alliances would grow faster than other international groupings. While these data indicate that EU MNEs are increasingly engaging in STP as a means to acquire and develop technological assets, the data also indicates that the establishment of the single market, which should have led to an increase in the number of intra-EU alliances, has not had an appreciable effect on the propensity of EU firms to engage in strategic alliances. In fact, there has been a decline in the number of intra-EU alliances since the mid-1980s. EC 1992, on the basis of this casual analysis of the data seems to have led to an increase in the number of alliances between US and EU firms, rather than between EU firms.

Table 6.3. gives the equity-contractual arrangement ratio, where this ratio expresses the number of joint ventures set against the number of contractual arrangements for each of the three inter-regional groupings for the period 1980-1993[8]. A ratio of '1'

[8] Given annual as well as sub-period irregularities we present these ratios for the period as a whole.

would indicate that both modes of cooperation are equally important. Table 6.3. shows that most of the international alliances are of a non-equity type. However, there are significant differences between the four groupings. For intra-EU and US-EU partnerships, joint ventures are a small minority of the total of strategic technology alliances. The significantly higher ratios for Japanese-US alliances and Japan-EU alliances indicate that partnerships with Japanese companies are more frequently governed by equity arrangements which offer a larger degree of control over technology sharing than non-equity partnerships. Table 1 would indicate that the preference for contractual agreements is at the same level as EU-US alliances, suggesting that EU firms are equally likely to engage in contractual alliances with a US partner as a EU partner. Once again this data suggests that the effects of the single market are not significant on the strategic alliance activity of EU firms. It would seem that the changes in STP are influenced less by regional changes such as EC 92 than by other global phenomena on a industry level, and by globalisation.

Table 6.3. Equity versus contractual partnership ratios, EU, USA, Japan, 1980-1993

Intra-EU (non-domestic)	*US-EU*	*Japan-US*	*Japan-EU*
0.37	**0.37**	**0.52**	**0.67**

Country specific characteristics of international strategic technology partnering

To what extent are individual EU countries engaging in technology partnering. By focusing on US-EU, EU-Japan and intra-EU alliances. we are in a position to appreciate the differences between countries, and evaluate the role of country specific characteristics in determining the propensity of their firms to engage in technology partnering. Theoretical and empirical analyses of R&D related foreign direct investment suggests that companies favour partners from countries that demonstrate comparative advantages in similar or related industries, both in terms of technological capabilities and infrastructure, and that also provide access to domestic and regional markets.

Table 6.4. presents the ranking of European countries in terms of their alliances with US and Japanese firms, the ranking of intra-EU, non-domestic alliances, the rank order of company R&D expenditures, their share of OECD high-tech exports, and their overall market size as proxied by Gross Domestic Product (GDP). The company R&D expenditures as a percentage of GDP and the share of high-tech exports in total high-tech exports of OECD countries represent, in our view, the most adequate indicators of the level of technological sophistication of a country as far as the attractiveness for inter-firm technology partnering is concerned. The latter indicator, the share of high-tech exports in total high-tech exports of OECD countries, actually combines country size with a technological strength indicator. It is to be noted that, to some extent, GDP is an imperfect measure of market size for countries such as those of the EU, due to the effects of economic integration. However, due to the differences between these countries in the extent to which their de facto market size is greater than that of their domestic market, and the difficulties in objectively estimating this, we will assume that their domestic market size represents their actual market size.

The rank order of countries for each of the three combinations of strategic technology partnering is quite identical with only marginal differences. These data combined with the indicators of technological sophistication and market size suggest that as far as strategic technology partnering is concerned there are three categories of EU countries:

- The first group with a high level of alliances consists of Germany, UK, France, which represent both a large market size as well as a high level of technology sophistication. In this group we also find Italy, which, although it has a relatively low R&D intensity, has a large market size, and the Netherlands, which is not only the largest of the smaller EU countries, but is also home to some of the most innovative and internationally competitive multinational companies.
- The second group with an intermediate level of technology partnering consists of countries such as Belgium and Denmark, countries that have a relatively small market but which are technologically quite sophisticated, as well as Spain that has a relatively large market but has a level of technological sophistication that is below the EU average.

- Finally, the third group consists of small and generally less technologically developed EU countries -Greece, Ireland, Luxembourg, Portugal - whose firms are scarcely sought as international partners.

Table 2 Ranking of European countries, strategic technology alliances with US and Japanese companies and intra-EU alliances (non-domestic), 1980-1993 (numbers), company R&D expenditures as percent of GDP (1990), share of high-tech exports and market size as GDP (1990)

	EU-US alliances	EU-Japan alliances	Intra-EU alliances**	R&D/GDP	Share of OECD high-tech exports	Market-size, GDP 1990, $ billions.
1	UK (259)	UK (75)	France (236)	Germany 2.02%	Germany 14.6%	Germany 1,692
2	Germany	Germany (70)	UK (220)	France 1.48%	UK 9.2%	France 1,168
3	(248)	France (61)	Germany (215)	UK 1.47%	France 7.8%	Italy 1,072
4	Netherlands	Netherlands	Netherlands	Belgium 1.23%	Italy 4.6%	UK 964
5	(182)	(52)	(171)	Netherlands 1.16%	Netherlands 4.2%	Spain 487
6	France (176)	Italy (32)	Italy (138)	Denmark 0.85%+	Belgium 2.0%	Netherlands 279
7	Italy (114)	Belgium (9)	Spain (48)	Italy 0.76%	Ireland 1.8%	Belgium 192
8	Belgium (24)	Spain (3)	Belgium (46)	Ireland 0.55%	Spain 1.2%	Denmark 122
9	Spain (14)	Denmark (1)	Denmark (14)	Spain 0.47%	Denmark 1.1%	Greece 66
1	Denmark	Greece (0)	Portugal (2)	Portugal 0.12%++	Portugal 0.3%	Portugal 58
0	(12)	Ireland (0)	Ireland (2)	Greece 0.10%+	Greece	Ireland 38
1	Luxembourg	Luxembourg	Greece (1)	Luxembourg -	0.1%	Luxembourg 12
1	(4)	(0)	Luxembourg (0)		Luxembourg - #	
1	Greece (1)	Portugal (0)				
2	Ireland (1)					
	Portugal (0)					

* equity and contractual agreements, excl. minority holdings

** these alliances are actually dyads

\+ 1989

++ 1988

Research Findings on the internationalisation of technology

Results deriving from CATI tend to be most relevant to technology intensive, 'core' technologies given the biases of the database. Nonetheless, since these are the same industries which experience high growth, issues relating to these sectors have broad policy implications for EU industry as a whole. As Figure 3 illustrates, the growth of strategic technology partnering has demonstrated the growing need of leading companies to seek corporate flexibility in their acquisition and development of new technologies. These are partly in response to the forces of globalisation.

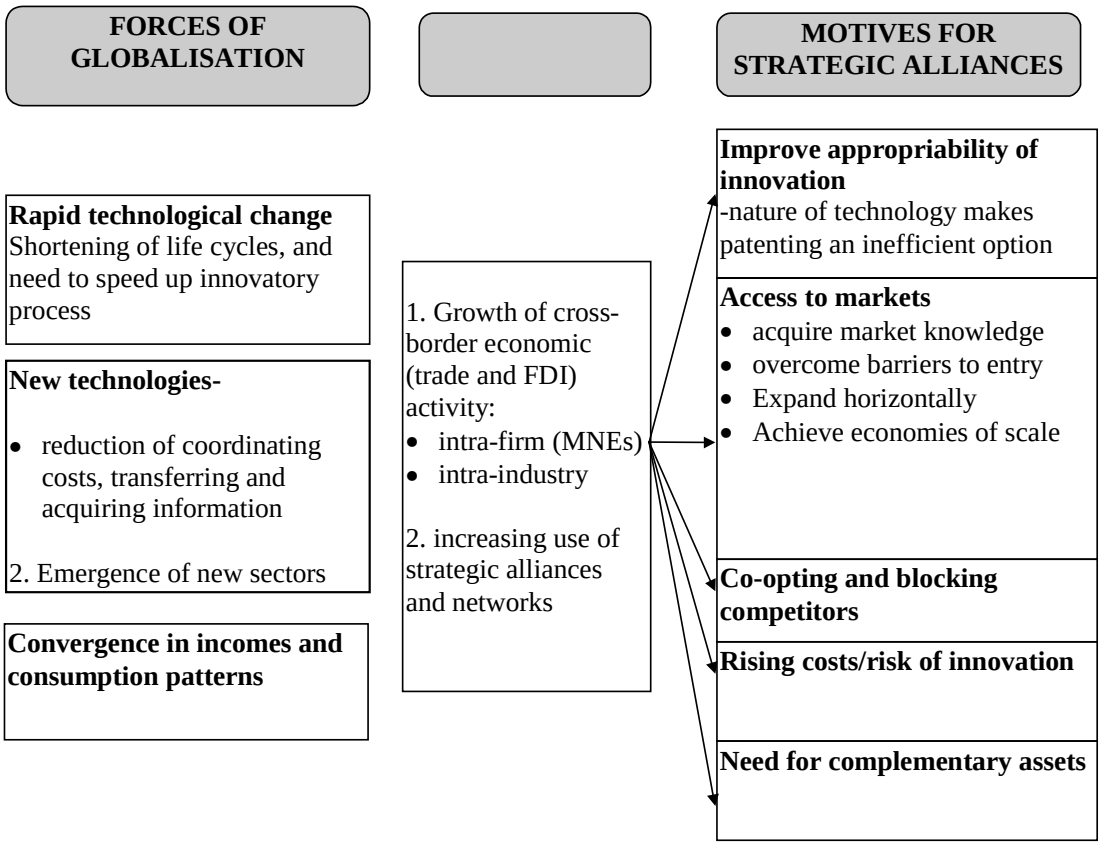


Figure 4: Relating globalisation to the motives for strategic alliances
Source: Narula and Dunning (1998), based on Hagedoorn (1993a, 1993b), Dunning (1993), Narula (1996b), Glaister and Buckley (1996)

However analyses (Duysters and Hagedoorn 1996) clearly suggests that the importance of strategic alliances in the internationalisation of the economy should not be over-stressed.

There are numerous costs and risks associated with strategic technology partnering. Well over 50% of all alliances are believed to terminate unsuccessfully. In addition, there are huge costs associated with operating alliances, due to the infrastructure and management requirements that they represent. As such, strategic technology partnering very often tends to be the domain of large MNEs rather than small and medium enterprises (SMEs). Even where strategic alliances involve SMEs, this often leads to an acquisition of the SME by the large firm. Hagedoorn and Sadowski (1996) note that about 2.6% of STP has lead to M&A, a relatively high percentage given the failure rate of technology alliances. This may seem to be a relatively small number, but if one keeps in mind the high failure rate, this is quite a significant level.

It is also worth underlining that the idea that strategic technology partnering is NOT a means by which developing countries or peripheral regions may achieve technological catch-up. Two studies based on the CATI dataset, one by Freeman and Hagedoorn (1994) and the other by Narula and Sadowski (1998) have examined the involvement of STP by developing country firms. The results indicate that their participation is very limited, and in general STP is an activity that is most effective for large MNEs from the most industrialised countries, a fact confirmed by Table 6.4.

One of the primary lessons from this stream of literature seems to be that STP does not represent a substitute for indigenous technology development, but exists as a complementary means to acquire or develop technology. Firms at the technological frontier prefer to partner with firms that possess skills or technology which is also cutting edge. They are loathe to share technology with firms that are technologically inferior to them. As several researchers have pointed out, firms are seeking to pre-empt the innovation of new technologies by other companies who are in a race to be ‘first’, since new technologies have a rapid rate of innovation, and thus the only way to have a technological advantage is to be first to innovate. Firms that do not innovate are not attractive partners for STP, and this points to the necessity of advanced technological infrastructure that is often associated with national systems of innovation.

Shortcomings and areas for additional research

An area that had been studied in great detail- that of motive of STP- in the CATI dataset and provided important results was discontinued from 1989. The main motives, described in table 4, suggested considerably different structure of motives for different sectors. Due to the high cost of monitoring these agreements and determining the motive, this has been discontinued. This is an area of considerable interest to policy makers, especially when examined on a time-series basis. This line of research would help to better examine the reasons for alliance failure, and the means whereby the longevity and success of STP might be improved. However, this is best done on a case-study basis, which could be linked to CATI, so as to make a more complete picture.

A second database needs to be developed with additional information on non-core technologies. Although core technologies have a long-term significance, these account for only a small percentage of total STP. The picture developed by CATI may be a little-one-sided. However, in order to do so on a long-term basis, so as to be backwards compatible, and on a time-series basis, may be prohibitively costly. Likewise a similar and complementary database on non –innovatory activity strategic alliances would be useful. Although several of these exist, they use different methodologies and are not available on a time-series basis.

3. THE NIS-2 INNOVATION COLLABORATION SURVEY USING CATI[1] METHODOLOGY

Theoretical and analytical background

This section describes a large international project to collect survey data in innovation co-opertion. The first collaboration survey using CATI methodology was developed in Denmark by Bengt-Åke Lundvall and his collaborators at the IKE-group in Aalborg as part of their larger DISKO[2] project. The effort appears to have been motivated partly by theoretical concerns springing out of the national innovation systems approach, and partly by empirical results from and experiences with the first Community Innovation Survey (CIS). The core idea behind the approach is to identify and describe collaborative links between business firms and surrounding organisations in their efforts to develop innovations.

The approach was brought into OECD work on empirically mapping national innovation systems as one of the focus group activities. In this context, and after quite extensive revisory work, the survey with some national variations has been carried out also in Austria, Spain and Norway. Work is under way also in Sweden (regionally), Australia, France and Italy.

An important result from modern innovation research is that it has brought forth firm support of the claim that innovation happens in interactive processes of development and learning[3]. There is no simple uni-directional flow of knowledge from the depths of pure science and into the economic realm of production and exchange; the process is interactive and may originate at any point in the chain, often without involving science at all. Thus, the long held view that economically important innovations have their origins in advances in science and that alone is flawed. Innovation has its roots in complex collaborative set-ups, where scientific and technological developments certainly may be important, but where also the striving of business firms to develop their activities and their markets play a decisive role.

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[1] CATI is shorthand for Computer Assisted Telephone Interviewing.

[2] Det Danske Innovasjonssystem i Komparativt perspektiv.

[3] See for example Edquist 1997.

The new insights imply that innovation rarely happens inside isolated single firms, and that collaboration between firms, and between firms and other types of organisations, are extremely important as creative efforts are undertaken. However, there is a lack of specific knowledge concerning the extent of such collaboration and the nature of the interactions that take place. More specific knowledge about this is crucial for furthering our present understanding of innovation.

As we advance our analysis of innovation beyond the linear model we need to confront one very important implication. If innovation is the result of collaborative development and interactive learning, then innovation must be the outcome of the workings of a system, and not of the efforts of isolated actors. In other words: The individual actions that bring forth innovation must be understood as actions of individual members of a system. The actions have an important cultural dimension – and this cultural dimension is as important for the analysis of innovation as is the individualistic and maximising dimension of actions. The explanation of innovation processes and results cannot but take seriously the social context within which innovation is carried out. The institutional context (both the cultural and organisational dimension of this context) has significant impact on innovation, and are necessary parts of any explanatory scheme that aspires to account for any specific instance of innovation.

This is important both for theoretical and empirical reasons:
(i) In the efforts to clarify the nature of innovation in modern economies, empirical knowledge about firm behaviour with respect to collaboration is pertinent. Theories about economically relevant action often rely on an individualistic meta-theory about social reality: Social action is but the aggregate of individual actions. Furthermore, important social-science traditions builds on conceptualisations of individual actions as rational and optimising action, as actions designed to attain specific purposes for the acting individual. The concept of innovation as "maximising the economic returns of new scientific discoveries" is obviously part of the rationalistic and individualistic tradition in social science. The concept of innovation as "interactive learning in a social context" is not. Thus, doing research on collaborative behaviour in innovation promises to give new insights with relevance for this fundamental and long lasting theoretical debate within social science.
(ii) When we realise that the context of innovative behaviour is a crucial determinant of the course and content of innovation processes, it becomes clear that comparative analysis of

innovation efforts in various regions and countries would be of utmost importance. Comparative data would appear to be the only way to get reliable knowledge concerning the regional and national specificities of the socio-technical, organisational and institutional (and cultural) contexts which have such a decisive impact on the overall innovation performance of an economy.

The data gathering approach

The Community Innovation Survey (CIS, 1992/93) and the Policies, Appropriability and Competitiveness for European Enterprises Survey (PACE, 1995) were cross-European efforts aimed at this kind of data gathering. These were rather general, first attempt surveys. The joint effects of conceptual vagueness, difficulties in developing an acceptable questionnaire adequate for all countries, and low response rates, led the CIS dataset to suffer from limitations with respect both to data reliability and comparability of data from the different countries[4].

The collaboration survey using CATI methodology aimed at creating a more focused data set, concentrating on gathering as comparable data as possible on issues only related to collaboration during the innovation process. Reflecting this ambition, the group behind the first iteration of the survey, the Danish DISKO project group, developed a more effective data gathering methodology than the conventional paper questionnaire survey method. A concise set of questions, with mainly yes/no/don’t know response options, was implemented in a computer assisted telephone interviewing system (CATI).

Through work in the OECD NIS2 focus group that was established during 1997, a common approach for empirical work in all participating countries was agreed upon. The aim was to try to bridge the gap between the increasing focus on the collaborating, network-embedded firm on the one side, and the lack of systematic empirical data on how, why and with whom firms interact in product innovation on the other.Compared to the first DISKO version of the survey, the questionnaire was somewhat expanded in order to get more information on the contents of collaboration and factors shaping its establishment and mode of operation.

[4] Christensen and Rogaczewska 1998, page 3.

The advantages of the telephone interviewing approach are considerable. Compared to face-to-face interviewing, the resources needed are very much smaller, and at the same time, not very much is lost with respect to the processing of answers, between listening to answers and coding them into data tables. In comparison with mailed questionnaires, the telephone interviewing method is significantly more powerful, since most of the coding responsibility is transferred from the respondent to the interviewer. The experience in the Norwegian research team is that in spite of careful wording and the careful approach used when introducing complexity into the questions, the control gained over the interpretation of questions and answer alternatives is extremely important. There is in addition a huge data-quality gain inherent in keeping the interviewing job in-house by letting the researchers themselves do a significant part of the interviewing job and to use these experiences during analysis[5].

The questions asked

The result of the joint efforts to develop a common set of research questions was a compromise: An agreement was struck to use a set of common core questions, while opening up for the different national teams to implement their own modules in addition to the core questions. The collaboration survey was designed to cover a random sample of manufacturing firms. It is focused on product innovation, leaving process innovations and organisational innovation aside at present.

The core questions covered the following themes:

basic information about the firms

Data on the size of firms, number of employees, turnover, industry type etc. were generated by the different national teams. As a rule, such data were found in (or could be linked to) the databases from which the sample of firms was drawn.

Innovativeness:

The firms were asked whether they during the last 3 years had introduced onto the market any technologically new or significantly changed products, or had been working to do this,

[5] An implication of this is that even if great care was taken to develop a set of core questions common for all participating national research teams, the actual interpretations and assumptions made would necessarily reflect national and cultural specificities. Thus, comparability of data is even in this case not a given. It is important to consider to what extent national teams found similar problems, and found similar solutions to the difficulties that were encountered.

started to sell any new or significantly changed services (sold part and parcel with the manufactured products) and been involved in collaboration with other companies or other organisations during the innovation process?

Collaboration partners:

What kind of partners has the firm collaborated with on product development? Which of the partners are parts of the same corporation as the firm interviewed? How often does the company collaborate when it is engaging in product development?

Collaboration purposes and significance:

What was the objective of the single most important collaborative development project in your firm during the last 3 years? How many man-years have your company invested in this project, and how long has it been going on? Which types of partners were involved, why did you choose to collaborate with them, and how important did they turn out to be for the project as a whole? Have your firm collaborated with the same partners earlier, in case for how long? Did you make a formal contract with them concerning sharing of costs, secrecy and/or sharing of profits resulting from the development effort? How many persons were involved in the collaboration on the partners side? Has the collaboration so far resulted in an innovation introduced onto the market? Did the project as a whole keep budgets in terms of money and time?

Transfer of knowledge

In the Norwegian and Swedish cases a particular question on mechanisms for transfer of knowledge and/or other kinds of results were added. The respondents were asked to evaluate the importance of 9 specified categories of transfer mechanisms for each kind of partner.

Some preliminary results

Preliminary results of the Austrian, Danish and Spanish surveys are available. In addition, some results of the Norwegian survey can also be anticipated[6]. Table 6.5. lists the sample sizes for these countries.

[6] Christensen and Rogaczewska 1998. A report on main results of the Norwegian CATI survey is planned to be made available as a STEP publication in September 1998. (In general, STEP reports can be downloaded from the Internet on http://www.sol.no/step/)

Table 6.5: Sample sizes and innovation rates in Austria, Denmark, Norway and Spain

	Sample size	Introduced new product (% of sample)
Austria	1006	425 (42)
Denmark	1022	548 (54)
Norway	~1200	n.a.
Spain	398	310 (78)

In general, data provide strong evidence that innovation to a large degree happens in collaborative set-ups. A large majority of firms report that they do collaborate when undertaking innovative efforts and the tendency to collaborate seems to be stronger in larger firms. In general, collaboration within a country appears to be markedly more important than collaboration with firms and other organisations in other countries. The growing complexity of the knowledge base and the more rapid rate of change seems to make it attractive for most of the product innovating firms to establish selective relationships which are medium to long term. For instance, preliminary results of the Danish CATI data reveal that of the firms having collaborated with one or several partners over the last 2 years, only a minority were collaborating with these partners for the very first time. In addition, more than 70% of Austrian collaborating firms fully agree that trust and confidentiality is a very important basis for collaboration. The evidence of inertia in terms of stability and continuity in the network formations and clusters seems to suggest that it takes time and resources to build efficient communication channels which seemingly rest on factors such as shared culture, personal experience, and individual, mutual trust.

Data also indicate that manufacturing firms are increasingly prone to interact with knowledge-intensive service firms. Between one third and one half of manufacturing firms nurtured cooperative links with consultancies, technological service firms etc.

Quality of data

How comparable are the data, and how valid are they? As mentioned earlier, the interviewing method secures a much better way of getting hold of information than what is possible with mailed questionnaires. The dialogue which takes place in a telephone conversation secures a level of common understanding, and secures a significantly higher level of data validity than what one can expect from standard questionnaires. Also, it proves to be much easier to get in

contact with people using telephone interviewing. The response rates are generally good; but it adds to the validity of data when the analysts themselves have carried out a substantial part of the interviewing effort. This gives a very close understanding of the questionnaire, and any terminological or conceptual difficulties that the wording of questions brings.

There are three potential pitfalls worth mentioning with respect to the CATI based survey on collaboration:

First, that the challenges facing interviewers are considerable, both in presenting their case to the firms selected, and in actually carrying out the coding work which makes it possible to bring answers over to data in the computerised questionnaire. It is extremely important that interviewers are familiar with the structure of the questionnaire, what the questions are precisely, and what kinds of answers are wanted.

Second, and this obviously is related to the first issue, there are real terminological and conceptual challenges inherent in the questions asked. What is collaboration – when does interaction become collaboration? Is it enough to buy components from a supplier one or more times, or is some kind of interactive process involved beyond the exchange? What is technologically new, when a company is producing food products? Is a shipyard producing a technologically new product when it is building a large ship of a shape or size that it hasn't produced before? What is product development in a newspaper publishing company?

Third, there is a difficulty in handling the complex organisational structure of modern manufacturing industry. There is a problem in determining at what level to approach conglomerate firms and corporations: How should holding companies for manufacturing firms be dealt with? When a company is called, but say they only are a part of a larger structure and that it is meaningless to ask them about product development, what do you do with that? In general, how do you handle that for a significant subset of firms?

Answers for these questions can be worked out, and they need to be worked out in the course of the survey and subsequent analysis. Nevertheless, it is hard to secure that these kind of issues are resolved in the same ways in different countries. Also since the questions themselves are translated into the different languages of the participating national teams, and this translation in itself is a more than a trivial task, there will obviously be some level of

uncertainty associated with the comparative analysis that results from the collaboration survey exercise.

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