Measuring Scientific Productivity In Co-Citation Clusters

by

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(ABSTRACT)

This research examines scientific productivity among authors in natural scientific reference groups. A broad literature review surveys models of knowledge production, including measures of scientific products at different levels of abstraction. Data is drawn from authors in ten specialty areas, elites identified by co-citation analysis. These co-citation clusters are analyzed in general, in disciplinary sets, and as specialty groups. Results show that variance in the productivity of elite authors is not predictable on the basis of stratification variables. Descriptive differences in disciplines and specialties reflect contextual diversity in the social production of scientific knowledge. Differences in average annual paper publication, citation and highly cited paper publication do not correspond to differences in career age, job sector or prestige of highest degree. In general, stratification by experience and afilliation is not reflected in the variation of bibliometric measures of scientific productivity. This suggests that co-citation clusters are partially comparable to general populations of science, since author productivity is not simply predicted on the basis of social stratification for either type of population. Co-citation cluster authors are heterogeneous, like scientists in general, and their bibliometric differences do not correspond to variation in experience or afilliation.

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1.0 PROBLEM STATEMENT

This study begins with the problem of understanding and explaining natural scientific knowledge production as a sociological process. This problem is studied empirically through the examination of elite reference groups in scientific specialty areas. The goal of this research is to measure and explain scientific productivity among authors in co-citation clusters, bibliographically linked reference groups identified as central elites in natural scientific specialty areas.

In order to understand scientific productivity, research must consider studies of knowledge production at a number of levels of abstraction. Different models of knowledge production require different sets of indicators to measure the production of knowledge. Once operationalized, the problem becomes explaining variation in scientific productivity measures, using sociological information. Independent measures of career age, job sector and prestige of highest degree may contribute to variation in the degree of scientific productivity measured for elite, central scientific authors.

Research on this topic must use both conceptual measures from studies of scientific productivity and structural models of scientific organization to examine the potential for measuring productivity within elite groups of scientific authors. Social studies of science has spread since the development of modern theory concerning the structure of scientific research and change (Kuhn 1970). Structural models have been proposed to account for scientific activity and change as a social and cognitive process (Mullins 1972). Structural analyses sometimes assume economic models of scientific production in order to test hypotheses about scientific social structure (Machlup 1962). Studies of research productivity assume administrative or national models of social organization, in order to define and describe scientific performance (Irvine and Martin 1984a). The scientific productivity of individual researchers and social groups has been measured by sociologists and science analysts using a variety of indicators, most frequently bibliometric measures of scientific output (Garfield 1979).

Analysis of bibliometric ties between scientific authors indicates that scientific specialty areas may be modeled as elite groups of published researchers, identified as co-citation clusters through co-citation analysis (Small and Griffith 1974). Members of some co-citation clusters have been shown to have a characteristic group structure. They have been found to be younger and no more prominent than the general population of a specialty area (Mullins et al. 1977, Hargens et al 1980). This study further articulates the attributes of co-citation clusters by measuring the scientific productivity for a number of these reference groups. Research also examines the correlates of scientific productivity, considering how these measures and relationships may vary across disciplines, while recognizing the limitations of bibliographic measures of knowledge construction.

This study benefits from attention to several orienting strategies, representing different approaches to understanding scientific productivity. First, traditional american sociology of science has looked at scientific productivity in terms of the stratification and reward systems of science (Merton 1973). Second, structural analyses of scientific areas have looked at scientific organization and development, as its techniques have increased the possibilities of macro-sociological modeling (Mullins 1972). Sociology of knowledge considers how construction of results affects the form and value of the knowledge product at a micro-sociological scale (Knorr 1981). Finally, evaluation research examines scientific productivity or research performance in order to assess and rank scientific research groups or projects (Martin and Irvine 1985, Irvine and Martin 1984b).

Some scholars have emphasized the need for more cognitively oriented studies of science, to study the content of science as well as its inputs and outputs. For example, Studer and Chubin deride some superficially oriented studies as the "phrenology" of science, which ignore its cognitive content (Studer and Chubin 1980). Although it is not within the scope of this study to describe the construction of knowledge in detail, this is an important concern which will be used to critique studies of scientific productivity.

The general process of knowledge production takes place at a number of concurrent levels of abstraction. Micro-sociological inquiry had emphasized that knowledge is contingent upon the local circumstances of the laboratory. Studies of scientific production at a more general level have examined social structures and processes which take place within scientific communities. At a larger, societal level, studies of knowledge distribution dissolve the artificial barrier between "internal" and "external" realms in science, examining the role of knowledge and science in society. This study will explore the social process of knowledge production within limited, bibliometrically defined specialty elites.

1.1 GOALS OF RESEARCH

This research will explore conceptual models of scientific productivity, which may be used to examine the social character of members of co-citation clusters. A co-citation cluster is a theoretical reference group identified through bibliographic research. This research will examine the social process of scientific production in traditional terms, applying the concepts of stratification studies and evaluation research to a non-traditional social structure, the co-citation cluster. If these social networks are important for understanding scientific structure and change. then research must examine their productivity in terms previously confined to university departments or research institutions.

This study has two major theoretical goals. First, it will will critically examine models of scientific productivity in the literature. Stratification studies, structuralist sociology, constructivist theory and evaluation research all use concepts of scientific productivity, though with different definitions and operationalization. Each of these perspectives studies different scientific organizational forms, at varying levels of abstraction. Second, this study will discuss extend the concept of scientific productivity to be useful in the context of scientific reference groups. This is important since any model of the stratification and reward systems in science revolves around a conceptualization of scientific production (Merton 1968, Latour and Woolgar 1979). If elite networks of scientific authors are considered are to be important social structures in science, then research should measure their productivity and its correlates.

The empirical goal of this research will be to test the conceptual model developed from the literature review. This study will examine elite scientific networks, reference groups which were previously identified by co-citation analysis (Mullins et al. 1977, with permission). The data come from questionnaires sent to authors who appear on lists of highly co-cited documents (Small and Griffith 1974). First authors of cluster papers and co-authors of more than one cluster paper were sampled and sent questionnaires in 1975 (Mullins et al. 1977). This study will examine how stratification variables, career age, institutional prestige of highest degree and job sector, affect variation in average annual production of natural scientific papers. It will consider authors from ten specialties, publishing over a period of eleven years before 1976.

This study will operationalize scientific productivity in several ways. First, scientific productivity is measured in terms of the average annual number of recognized published papers. This is a standard measure in the science studies literature. Second, two different measures of an author's research "quality" or perceived significance will be used. Measures of average annual citations and highly co-cited papers will show the impact of an author's papers, the response of a scientific community to an author's products. The study also tests for the convergence of scientific productivity indicators (Rogers and Lieverow 1986; Irvine and Martin 1984).

These variables are important to both sociologists studying social stratification and productivity in science (Allison and Stewart 1974, Andrews ed. 1979), and to academic research management studies (Walton et al. 1986). This study will identify stratification variables which may correlate with various measures of scientific productivity and test hypotheses about these relations using descriptive, bi-variate and multiple regression analyses. Independent variables will be selected from the data to reflect structural conditions affecting research productivity. Analysis of the effects of career age, job sector and institutional prestige variables will attempt to explain variations in several indicators of scientific productivity.

The second chapter of this study will review the literature on scientific productivity, examining different theoretical perspectives and methodological directions. It will discuss models of knowledge production, studies of different organizational forms, bibliometrics, and the criticism which responds to these topics. Chapter three will give the methodology for empirical study, including the population and the data set, and the statistical methods applied. Chapter four will show and interpret the results of analysis. The final chapter will discuss the meaning and implications of this research, concluding with ideas for the future.

2.0 LITERATURE REVIEW: SCIENTIFIC PRODUCTIVITY

As individuals and groups, teams and institutions, specialties and disciplines, natural scientists produce results which are selected, organized and shared in a social process of knowledge production. Sociologically, the production of knowledge may be examined at many levels of abstraction, in a variety of organizational contexts, and using a wealth of indicative measures. This chapter reviews an array of literature on scientific productivity, ranging from theoretical studies of knowledge production to empirical studies of scientific groups. A review of theoretical views includes topics which have been labeled constructivism, structuralism, functionalism, evaluation research, and economic models of knowledge production. Empirical strategies include bibliometrics, stratification studies of scientists, cognitive group studies, institutional and national studies of scientists. Critiques of productivity studies conclude the review of literature on scientific productivity.

2.1 THE PRODUCTION OF KNOWLEDGE

The general social process of knowledge production is most specifically examined as the construction of knowledge forms (e.g. data, results, facts, papers), which takes place in the locally situated context of a laboratory. This process, studied by the constructivist program in the sociology of knowledge (Knorr-Cetina 1983), focuses on micro-sociological interactional processes which select and interpret the products of science in the first instance.

Second, production of knowledge forms (e.g. papers, books, references, proposals) takes place in a university department, a research center or scientific institution. Production will be used to describe a broad range of activity within the scientific community. Studies of scientific production measure the degree to which a scientist or research team puts out viable and interesting results. This abstraction of the scientific process will be the central focus of our study.

Finally, there is extensive dissemination and utilization of knowledge forms (e.g. papers, reports, information) throughout different branches of society (e.g. government, industry). These are broader aspects of knowledge production. Many forms of analysis at this level raises questions of information transfer and processing at a larger social level, external to the scientific community and beyond the scope of this study.

This study will consider several definitions of knowledge production in the literature. In constructivist terms, knowledge production is an act of locally situated, reflexive fabrication of data. Knorr advocates the study of fact production over the study of the way in which knowledge represents nature.

> Laboratory studies demonstrate that scientific products are "occasioned" by the circumstances of their production "Occasioned" here means that the circumstances of production are an integral part of the products which emerge. (Knorr-Cetina 1983:124)

Production and product are integrated in the constructivist explanation of scientific work. One problem with constructivist views of production is that the products are examined in detail instead of as a part of a whole, and the variable inputs and outputs of the project lose general significance. Construction of scientific products in the laboratory is a microcosm of the more general production of knowledge, which is measured in micro-sociological models.

In economic terms, production in science means that a valued input results in a valued output (Machlup 1962:39). This definition is most widely used in science policy analysis (OTA 1985; Irvine and Martin 1984b). Indicators of input and output are measured to discover the relative performance and efficiency of a scientific group, a scientific institution or an entire specialty. This opens up avenues for evaluation research to examine social units of knowledge production. The method of converging indicators, or triangulation in sociological terms, is useful in measuring knowledge production. The primary problem is to find valid indicators of inputs and outputs at individual and structural levels of organizational abstraction.

Knowledge can be considered as a cost or a product in economic terms, as an investment or a consumer good. "Knowledge can be classified either as a final product or as a necessary requirement-cost element in the production of other goods and services." (Machlup 1962:29) If knowledge is useful, it must have a position in the exchange relations of our society. In this perspective, scientific production is considered a black box and knowledge is one of many inputs to and outputs from production. Knowledge as an investment or return is not simply evaluated, however. "The principle benefit of research, especially basic research, is new and often unexpected knowledge, which cannot be assigned a direct economic value." (OTA 1985:4) Modeling scientific funding as an economic investment is useful only as an exercise in some cases, since

> improving productivity or producing and economic return is not the primary justification for most federal R & D programs...The very concept of measuring the return to Federal investment is therefore inherently flawed. (OTA 24)

Measuring investments and returns in knowledge production is difficult because of the liquid, esoteric nature of knowledge.

Social structural models view knowledge production as it links networks of scientists. Citation and co-citation analyses are frequently used tools in the empirical examination of scientific clusters

(Small and Griffith 1974; Mullins 1977; Garfield 1979). Social structure can be also be developed based on patterns of communication, independently of cognitive structure (Rogers and Lievrow 1986:31). This view relies primarily on bibliometric measures of science, especially the published paper. It is a powerful, though limited tool for analysis of scientific production, and it is especially useful as one of several converging methods.

Some authors argue that information, the content of knowledge, is not its only attribute. The value of knowledge is related to its holder and its currency in social structures:

> The usefulness of information has more to do with the characteristics of the person (or persons, ed.) who possesses it (i.e. an expert) than it does with the substance of the message that is being conveyed. (Rich 1979:28)

More specifically, production of knowledge creates problems of linkages and communication within scientific communities. How can ties between knowledge producers be drawn and measured? These problems require empirical research on scientific networks (Mullins 1977, Rogers and Lievrow 1985).

There are analyses of social organization in science at numerous, often overlapping and conflicting levels of abstraction. The resources, products and goals of science selected for study depend on the level of abstraction considered. Authors look at individual scientific careers (Long 1978), cognitively tied groups like co-citation clusters (Mullins et al. 1977), or large experimental instruments and research institutions (Irvine and Martin 1984). In examining scientific productivity as a dependent variable, the utility of indicators will depend on the level of sociological abstraction and the structural model used. At each level there are specific inputs and outputs associated with the productive process.

2.2 *SCIENTIFIC INPUTS AND OUTPUTS*

The productivity of any scientific work may be defined as the relation between a variable set of inputs and of outputs. These variables may be considered as investments and consumptions, within limitations (e.g. that federal research funds cannot be measured solely as investments in research products). The problem is to link these inputs and outputs, and not simply measure them as if they were independent of their means of production.

Financial inputs to research may be measured in terms of grants and contracts, which supply funds for institutional overhead, machines and salaries Knowledge comes in the form of education or training, as well as papers and other publications. Labor is measurable in the number of employee-hours in the scientific, operational and administrative branches of the experiment. Organizational management skills are necessary to a productive research organization. Capital investments in durable goods, such as laboratories and experimental equipment, are also necessary inputs. (Snizek and Fuhrman 1985).

Technology per se will not be considered in this study. However, technological "spin-offs," products which are accidental, often commercially viable by-products of research, are important to industry. For this reason, "spin-offs" or "fall-out" from research are quantified (e.g. in terms of numbers of patents), and forecast. "Positive effects, such as new products, may be called quality improvements. Productivity increases arising from challenges may be called secondary economic effects of research institutes" (Bianchi-Streit et al. 1985:24). In addition to measuring inputs and outputs of knowledge and capital, research may quantify an institution's economic "spin-offs", for example.

Publications, especially papers, are clearly a very important output, especially for academic scientists. Publications tie scientists into social and cognitive networks in their specialty areas (Mullins et al. 1977, Rogers and Lievrow 1986). Publications have been measured simply through publication counts (Hagstrom 1965). Papers will be considered the primary output of normal scientific work. Prestige and status are also important results of knowledge production, especially since there is evidence for a "Matthew effect," whereby attention and money are given to experts who have made a name for themselves or their group (Merton 1968).

Efficiency in scientific production is the maximization of outputs per unit input. Efficiency is a comparative measure. It is difficult, though possible to measure (Irvine and Martin 1984a). Measuring efficiency has the same problem as treating research funding as an investment, however. The purpose of research is rarely to be efficient, but rather to understand and explain phenomena, to create or disseminate new knowledge. At the same time, Parkinson's law may have an effect in scientific organizations:

> There is a ground for suspicion that some branches of the production of knowledge are quite inefficient, although it is difficult to ascertain input-output ratios and to make valid comparisons...the growth in the production of knowledge may be an instance of "Parkinson's Law," which implies that administrators tend to create more work for more administrators. (Machlup 1962:10)

The issue of efficiency is considered in terms of "performance" by Irvine and Martin, as elaborated below. Maximizing efficiency in science assumes wholly calculable inputs and outputs, which is problematic. Measures of efficiency are better suited to industrial production of technology than knowledge production in basic scientific research.

Scientific performance is a measure of productive efficiency in comparable terms. Performance measures rank individuals, groups or institutions against matched counterparts (Irvine and Martin 1984a). Competitiveness is inherent to research performance measures, which have some value in science policy. Similarly, impact is measured in terms of citations, sometimes engendering competition for citations (Moed et al. 1984).

The impact of a scientific work is variable and may be measured. The distinction between short-term impact, long-term impact and quality of scientific products is important. Short-term impact, measured in terms of limited-time citation counts, is related to a research unit's visibility, along with awards, invitations, etc. (Moed et al. 1984:22). Short-term impact measures are the most common and dynamic; impact can be operationalized for authors, author groups, articles and journals. This is the "splash" made by a knowledge product.

Long-term impact is less easily assessed for science policy. Enduring contributions are measured in terms of highly cited papers, although this measure has limits. Enduring contributors are often given awards (e.g. Nobel prizes), however the importance and impact of a paper or producer changes dramatically over time, as bibliometric analyses have suggested (Griffin and Small 1974, Moed et al. 1984).

Quality is an elusive attribute of research outputs. Bibliometric analyses assume a basic threshold of quality (in their selection of journals for reference), and peer review measures have been used to try to qualify quantitative measures. Cognitive, methodological and esthetic quality are suggested to be important, though slippery aspects of research products (Moed et al. 1984:24-5). In this study, quality will be measured as one aspect of scientific productivity, in terms of average annual paper citations and highly co-cited papers.

2.3 BIBLIOMETRIC ANALYSIS

Output measures of scientific productivity often rely heavily on bibliometric indicators, such as publication frequency or citation strength. Citation indexing has enhanced the utility and accessibility of bibliometric indicators, thanks to the Science Citation Index (SCI) and the Social Science Citation Index (SSCI) by the Institute for Scientific Indicators (ISI). Since written or textual accounts of scientific research are both the means of communication and the most visible goals, bibliometric measurement techniques tap the main arteries in the social production of scientific knowledge. They also form the basis for empirical clustering reference groups in science. This study will use measures of publication frequency and citation frequency in measuring scientific productivity, and co-citation analysis as the basis for the structural grouping of the social units in this research.

Citation analysis is the most popular method in bibliometrics. Explicit references in a published paper form linkages between members of scientific social networks, with minimal interpretation by the social scientist.

> Citations are the formal, explicit linkages between papers that have particular points in common...citations, used as indexing statements, provide measures of search simplicity, productivity and efficiency by avoiding semantic problems...the citation is a precise, unambiguous representation of a subject that requires no interpretation...in addition the citation will retain its precision over time (Garfield 1979:1-3).

Citation and publication indicators may also be used together, indicating the relative impact strength of a paper. For example, Irvine and Martin use citations per publication (CPP) and numbers of highly-cited papers (HCPs) to measure research performance. This measure introduces more complexity into basic indicators.

Co-citation analysis is a development of citation analysis which was originally developed to test hypotheses about the cognitive structure and linkages of scientific specialties. Co-citation clustering is a methodological development of Kessler's bibliographic coupling idea, which counts the number of references two documents have in common in order to measure the similarity of two papers. Similarly, co-citation strength measures the number of documents that have cited a given pair of documents in a given time period, reflecting the frequency of being cited (Garfield 1979:99). Co-citation clustering represents the variable status of a paper over time without distorting classification categories, and it helps analysts to map the cognitive structure of scientific areas (Garfield 1979; Small and Griffith 1974; Chubin 1980).

Co-citation strength is an indirect measure of quality of scientific production, since it reflects the relative importance of a linkage, and this linkage has an impact on the development of a scientific area. Central or pivotal papers as identified with co-citation analysis may be considered significant outputs, above and beyond highly cited papers. Co-citation analysis further provides a basis to interrelate research area structure and development with traditional stratification variables in science (Hargens et al. 1980:67).

Bibliometric indicators are useful for measuring scientific output at levels of production greater than individuals. This raises criticisms of bibliometric techniques. The Office of Technology Assessment (OTA) explains,

> Bibliometric techniques provide rough indicators of the quantity, impact, and significance of the output of a group of scientists' research. They are not generally considered valid for measuring the productivity of individual scientists due to differences in publishing styles and journal requirements, and the questionable validity of small statistical samples. However Cole and Cole, among others, have shown that publication counts correlate positively with other measures of individual scientists' research quality such as peer review, Nobel prizes and prestige of academic appointment. (OTA 1985:40)

A number of important criticisms of bibliometrics are noted and partially addressed by Irvine and Martin (Irvine and Martin 1984a:189). Publications make different contributions to the body of accepted knowledge, making some weighting of publications is necessary before simple counts are possibly valid measures of scientific performance. For example, one review paper doesn't have the same impact as one experimental paper. In addition, publication rates vary across disciplines and specialties. Therefore matched samples must be used for valid comparisons of scientific groups.

Criticism of citation analysis has three main points. First, there are technical limitations of the Science Citation Index (SCI) and the Social Science Citation Index (SSCI). Only first authors are listed, name changes which may cause imprecision in analysis are not easily detected, and there is the specter of clerical errors surrounding the Indices. Other forms of publications besides papers have not been consistently included in the Indices. Most importantly, only a limited number of journals are covered, requiring users to assume that the SCI and SSCI citations measure popular impact, not simply "quality" in some universal sense.

Second, there is severe ambiguity in the meaning of citations theoretically. Citations from a paper author may be critical, iconic or ritualistic, arbitrary, or imprecise. Self-citations are also a problem for user of bibliometrics, although some have replicated results controlling for these potential selfpromoting references. (Irvine and Martin 1984a). Bibliometrics are thus forced to assume the majority of all citations are genuine.

Finally, variation in the citation rate over the lifetime of a paper or across specialty areas can confuse bibliometric results. This problem may be addressed by using matched samples in analysis. This issue may also be addressed if citations are considered an impact measure, rather than a measure of quality.

2.4 STRATIFICATION STUDIES OF SCIENTISTS

Traditional sociological studies of productivity examine the stratification and reward system of science in terms of academic career variables. This research often measures productivity strictly in terms of output measures, especially publication and citation frequency. The results of stratification studies is a body of theory about social systems of individual scientists, in terms of career trajectories and theories of the cognitive structure of science. Much of this work can be traced back to Merton's classic functionalist account of the normative structure of science (Merton 1973).

In the mid 1960s, theorists Blalock and Duncan advocated causal modeling drawn from partial correlation and regression analysis, in order to draw broad pictures of social processes. "Once established in the sociology of science, the causal modeling approach fostered lines of inquiry quite similar to those it prompted in the wider discipline" (Hargens 1978, 126). These techniques complimented Mertonian studies of stratification in the development of american sociology of science.

Research on the stratification of scientists has a number of recurrent themes. Achievement, production and reward are common dependent variables, with different indicators for each variable.

Age, experience, prestige (individual or institutional), status, gender and ethnic group are independent variables which are used to predict variation in performance or achievement variables. Some early studies focus upon university departments, (Crane 1965, Cole and Cole 1967) while others look at specialty areas or disciplines (Hagstrom 1965). Social stratification studies look at the demographics of a population in science and relate these variables to a hypothesis which makes sense of knowledge production.

Stratification studies measure inequality in science, using differences in productivity, social status or demographics to explain different variations in scientific performance. For example, the accumulative advantage hypothesis suggests that highly productive scientists maintain or increase their productivity, while less prolific scientists lose ground over time, due to differential feedback of rewards such as recognition or resources. Merton calls the variable rewards based on differential reputation the "Matthew Effect" (Merton 1968). The Coles have generalized this hypothesis to include bibliometric measures of productivity (Cole and Cole 1973). Productivity is clearly related to resources and recognition, however causal patterns are difficult to establish empirically.

The accumulative advantage hypothesis may be considered an elaboration of the Matthew effect accounting for productivity as well as prestige (Cole and Cole 1973). It has been empirically verified as an explanation of productivity differences (Allison and Stewart 1974). This hypothesis argues that the distribution of productivity becomes increasingly unequal as a cohort of researchers gets older. The presence of this phenomenon supports the importance of both chronological and career age as aspects of productivity differences.

Mathematical formulations of the accumulative advantage hypothesis suggest its empirical implications (Allison and Stewart 1974:598). Productivity is related to esteem and resources at a given time, without postulations about causal effects. Bibliometric measures are used as converging indicators of productivity. Results of research on age stratified physicists, mathematicians and chemists show that inequality increases with career age in fields with high theoretical consensus, supporting the hypothesis of accumulative advantage over time (Allison and Stewart 1974:599). In the same study, this result is not replicated among biologists, suggesting a difference between disciplinary reward systems in scientific specialties, based on a degree of theoretical consensus.

Research on career age and scientific performance is also used to address questions about academic careers, and practical issues in educational or science policy. Researchers measure chronological age, career age (experience), or both. They are clearly highly correlated in all populations of academic scientists (Bayer and Dutton 1977, 265), and across job categories as well (Andrews et al 1979, 61). Research often plots bivariate relationships between career age and professional productivity, matching this relation to a mathematical function, or comparing this function across populations.

Career trajectories in all sciences are found to best fit "spurt-obsolescence" functions (Bayer and Dutton 1977, 272), supporting a hypothesis of "selective attrition" from academia (Bayer and Dutton 1977, 278). The shape of this relation is variable across disciplines and institutional categories. Academic scientists produce publications at a rate which is more highly variable over time than scientists in industry (Andrews et al. 1979, 62).

Studies of the effects of institutional prestige on scientific outputs are diverse. In university science faculty, institutional prestige is highly correlated with production (Hagstrom 1971), but this is not found when one author studies it as one of many socialization variables which affect early career performance (Reskin 1977). There is evidence that the effect of institutional prestige is constant across fields (Hagstrom 1971). However studies use institutional prestige as both dependent and independent variables. It is clear that it is an important variable, but it's role in a model of scientific knowledge production is not constant throughout the literature.

Research on the relationship between the stratification system and measures of productivity has also considered the historical effect of institutional affiliation and prestige on output measures of productivity. Long argues that this relationship must be examined longitudinally, over the course of a scientific career, since cross-sectional designs provide misleading results (Long 1978:891). Without consensus in this area, competing theories search for empirical support. The reciprocal effect of departmental prestige on productivity is studied both for doctoral graduates and practicing scientists.

Social stratification variables will be operationalized and specified in the following chapters. The present study will model career age, job sector and institutional prestige as independent aspects of stratification which may help to explain variation in different measures of scientific productivity. Other interesting variables considered in the literature, such as institutional position or "status", lie outside the potential of the data at hand. The variables considered will provide ample information in any case, which may be used to compliment findings in literature on stratification in science.

2.5 COGNITIVE GROUP STUDIES

Most studies of scientific productivity select levels of aggregation smaller than research institutions or large research projects. These studies fall into two categories: those which measure administrative groups, such as departments or research teams, and those which measure cognitively tied reference groups, such as scientific networks and co-citation clusters.

Studies of cognitively linked groups of scientists are primarily concerned with the structural configuration of specialty areas or research networks. These groups are identified using co-citation or co-word analysis of bibliometric data, and the shape and content of the group is of primary interest. Cognitive group studies assume a level of output productivity in order to identify their units.

An author's position in a cognitive elite, such as a co-citation cluster, may affect their future productivity:

> Being a central participant in the development of a research area a gives a scientist an advantageous position in relevant communication networks, which in turn leads to higher levels of subsequent scientific productivity (Hargens et al. 1980:56).

This point is illustrated with data on social networks using block modeling analysis, which shows that with greater sociometric centrality of a block come higher output and increased inputs in the form of research funds. The argument develops the accumulative advantage hypothesis, which theorizes that centrality in cognitive structures helps a scientist attract important resources which allow for higher scientific productivity. This hypothesis is supported by data from two co-citation clusters in microbiology, the discoveries of Australian antigen and reverse transcriptase. Position in cognitive structure is more strongly correlated with individual publication rates than common stratification variables (Mullins et al., 1977), suggesting that cognitive groupings are necessary in order to understand scientific productivity.

Many productivity studies select administrative units for analysis, with obvious implications for R&D management in academia and industry, as well as national science policy. There are examples from studies of academic departments, entire faculties, and "research units". Administrative units are the most clearly defined, though changing, units of research organization.

Moed and colleagues issue a comprehensive report on research at Lieden State University in Holland, examining the faculties of Medicine and Mathematics/Natural Sciences (Moed et al. 1984). Bibliometric indicators measure performance in terms of output and impact. Output is defined as the extent to which bibliometric research creates a body of results. Impact is defined as the actual influence of output upon surrounding research activities. Impact is operationalized in terms of number of citations to faculty group articles during periods between 1970 and 1980 (courtesy of the ISI), and the level of primary aggregation is the research group.

Factors disturbing analysis of scientific research groups include the fact that citation practices vary across fields. Also, citation practices can change within a field during a decade of work. Finally, the data base of the SCI is biased towards journals; books are not included until 1977. Even so, the Dutch analysts suggest that bibliometrics are useful as a monitoring device and as a basis for dialogue between policy makers and university research groups (Moed et al. 1984).

Scientific productivity among research groups is studied internationally by UNESCO research (Andrews ed. 1979). Six countries are studied both at the level of individual scientists and "research units". These units are identified as groups of at least three people expected to work together for at least one year, with one "unit head" devoting at least eight hours per week to common research. Research units are said to represent "a set of heterogeneous units drawn from a variety of national, disciplinary and organizational settings" (Andrews ed. 1979:25).

Research unit performance measures assume scientific production in multi-dimensional concepts, and that qualitative and quantitative information must be included. Measures of output and ratings of performance included a number of indicators. (Andrews ed. 1979:35). These include hefty measures of publications, patents and prototypes, reports and algorithms. A composite measure of effectiveness is drawn from qualitative evaluations, such that 41 variables are reduced to seven performance aspects. Performance aspects include measures such as "recognition accorded to the unit" and "administrative effectiveness of the unit". (Andrews ed. 1979:39)

Snizek and Fuhrman will look at four dimensions of scientific productivity among faculty scientists in a pilot study of two land-grant institutions. The single measure of input is involvement in sponsored grants and government contracts. Three measures of output are research publications, teaching contributions and consultant postions. The authors operationalize these variables using measures of communication and work routines, especially as facilitated by personal computers (PCs). They argue that variables of status, location, discipline and PC access indirectly affect scientific productivity, while reward structure, reputation and funding sources directly affect productivity (Snizek and Fuhrman 1985).

The consequence for scientific productivity studies is that cognitive structure must be integrated into both individual and group output measures. Scientific knowledge "seems to develop in spite of its formal and informal social structures." (Studer and Chubin 1980:100) Cognitively linked groups are as viable a productive unit as administrative groups, commonly used in policy analysis. Further, the content of knowledge itself must remain the focus of sociological research on science.

> The place of knowledge has been lost in the study of scientific growth. The centrality of ideas as a prime mover of rationale for research activity has been denied...the intellectual (content) must be used to inform the social (structure) in science (Studer and Chubin 1980:226).

Authors have done this by looking at the content of scientific research areas, not simply their structures and social processes.

Two limitations of cognitive group studies are their reliance on qualifiable measures of productivity and their focus on social structure, rather than scientific productivity as the object of study. Scientific productivity is assumed as a constant and singular process in the analysis of scientific social patterns. For this reason, it is logical to identify and compare measures of scientific productivity for cognitively tied units, using multiple converging indicators. The productive processes of different cognitive units are not always comparable, however.

2.6 INSTITUTIONAL AND NATIONAL STUDIES

At the most general level of sociological abstraction, studies of scientific institutions and major scientific instruments show large scale scientific productivity. This body of evaluation research has the potential not only to evaluate large research projects, but also to forecast the future, aiding R&D policy (Irvine and Martin 1984a). It also aids international comparisons of basic research (Irvine and Martin 1985).

In a series of papers, Irvine and Martin measure performance and forecast future prospects of CERN's contribution to world high energy physics (HEP). They use empirical indicators of relative performance in terms of productivity (input/output), impact (citation strength), and perceived significance of scientific research based on informed interviews. These indicators of performance are used to rank CERN in the world HEP community, both in terms of the institution and particular experimental machines throughout history (Irvine and Martin 1984b; Martin and Irvine 1984). Their work is explicitly directed towards understanding scientific productivity, as well as impact and perceived significance.

Irvine and Martin use funding and the number of CERN users as measures of input. The problem with funding measures is that different exchange rates over time make international comparison difficult. The problem with counting institutional scientific users is one of definition. Irvine and Martin exclude graduate students in their tabulations. The levels of each input indicator is ranked as a percentage of the world total. A cost-per-physicist ratio is calculated and ranked in the world total. CERN, proportionately largest in world inputs, has similar input ratios to other HEP institutions.

Output is measured through three types of converging indicators: publication counts, citation analysis and peer evaluation. Citation indicators include the total number of citations, citations per paper and the number of highly cited papers. Citation analysis is based on eleven international journals, conveying over 90 per cent of the material deemed important through content analysis. Though each measure independently is problematic, Irvine and Martin address potential problems with each method of measurement, assuming that converging indicators will approximate the productive output of CERN.

Productivity ratios are calculated in terms of output and input ratios in three forms: papers/input rank, citations/input rank and "impact"/input rank. "Impact" is indicated by respondents as perceived significance. Thus each indicator of output is measured by a single index of input. Irvine and Martin conclude that CERN has the strongest indicators of performance in the world, in terms of publication and citation measures, yet they are second to the SLAC program in terms of peer ranking and "crucial discoveries." Indicators of productivity do not converge, in the final analysis, necessitating interpretation of the results. Martin and Irvine suggest,

> even if its possible to obtain quantitative peer evaluation data...qualitative data are still absolutely essential if one is to insure that the various pitfalls associated with each of the bibliometric indicators are to be safely negotiated (Irvine and Martin 1984b, 209).

Problems of interpretation or the meaning of productivity measures are the most pressing question for the use of science indicators in research policy.

On the basis of converging indicators of research performance Irvine and Martin reach three sets of conclusions. First, CERN's overall performance record exceeds that of all other HEP institutions in the world, when experimental machines are considered units of analysis. Second, ratio measures of scientific performance show that CERN falls behind American labs (particularly SLAC) in cost effectiveness. Third, none of the critical discoveries in HEP between 1961 and 1982 were made at CERN (Irvine and Martin 1984b:281-2).

Irvine and Martin use the same method of converging partial indicators to examine the Isaac Newton Telescope (INT) in the United Kingdom. The authors give several precautions to their methods (Irvine and Martin 1983):

1. Indicators must be applied to user groups, not individuals.
2. A range of indicators must be applied to user groups.
3. Indicators are only meaningful when they apply to matched user groups.
4. Citation indicators reflect impact, not quality of research.
5. Only when partial indicators converge do they provide a reliable estimate of research performance.

Irvine and Martin are more judgmental in this study, assessing the relative failure of a large research project/instrument. Their work brings many critical responses, including charges of methodological inadequacy and rhetorical deceit (Krige and Pestre 1985, Moed and van Raan 1985, Bud 1985, Collins 1985). The most detailed criticism, from Moed and van Raan, is that the concept of convergence is poorly operationalized. The authors reply that their indicators are partial and limited, but the best possible in the circumstance. It remains for others to replicate and further develop methods of converging partial indicators, both in the interest of science policy and for the understanding of sociological measures of scientific productivity.

2.7 *PROBLEMS AND PROSPECTS*

Studies of scientific productivity measure quantifiable indices which fall into into certain conceptual definitions, such as performance, efficiency, or perceived significance. Returns associated with concepts such as "the common good" or "public welfare" are abstract and difficult to operationalize. Benefits in education and national security are equally difficult to quantify and measure, though they are important by-products of research. In the words of a government agency, "Economic returns are neither the sole nor the primary purpose for Federal research spending." (OTA 1985:3). Some aspects of scientific production are qualitative attributes more suitable for use in funding proposals than empirical measurement. The products of science address social concerns in so far as they generalize and theorize about the broader, external influences of research.

The industrial metaphor has limitations for measuring scientific productivity. Knowledge is reciprocal and esoteric, requiring that studies examine the diachronic nature of scientific production. Science is neither simply a black box nor a machine which consumes intelligent labor and capital and makes knowledge. The values of scientific labor and knowledge vary according to the

3.0 METHODOLOGY

This chapter specifies empirical methods for analysis of scientific productivity variables and independent measures of social stratification for authors in co-citation clusters. These methods are designed towards four objectives:

1. Operationalize the concept of scientific productivity based on measures of scientific output.
2. Test for the possible convergence of these measures of scientific productivity.
3. Examine similarities and differences in scientific productivity among and between scientists in clusters and sets of clusters.
4. Identify the importance of career age, job sector and institutional prestige of highest degree in predicting variation in different measures of scientific productivity.

The empirical analysis in this study is unique both in content and style. First, analysis of scientific productivity has not been conducted for all of the co-citation clusters in the data set described below. Second, studies of scientific productivity have previously been limited to organizational structures such as academic departments or institutions (membership groups), rather than cognitive structures identified through co-citation cluster analysis (reference groups). For these reasons the following empirical work is original analysis.

Co-citation clusters are reference groups for scientists, in both a sociological and literal sense. In the sociological sense, reference groups are the social bodies which people use to appraise and evaluate their feelings, attitudes and behaviors. They are groups to which a person is oriented, regardless of actual membership (Singer 1981:66). The concept of reference group was coined by Hyman, who hypothesized that an individual's assessment of their own social status is contingent upon a social framework for comparison (Hyman 1942). Subsequent research found that an individual may have multiple reference groups, which may be divided into comparative and normative functions (Kelly 1952).

Individuals use a variety of reference groups for evaluation of both self and others (Singer 1981). Co-citation clusters may be considered intellectual reference groups, as opposed to administrative membership groups, such as university departments. The people referenced in a scientific article are used by the author, readers and other evaluators to assess and compare the author. Clusters of co-cited individual authors form a reference group for authors in a specialty area.

This chapter provides a description of the population and data set. It then describes the dependent and independent variables for analysis, and the importance of these variables in the literature. This chapter concludes with a brief summary of the statistical methods employed to explain scientific productivity in co-citation clusters.

3.1 THE POPULATION AND DATA SET

The population for this research consists of elite authors who have appeared in empirically defined Institute for Scientific Information (ISI) co-citation clusters. The data set for this study has been made available by Dr. Nicholas Mullins. It was originally used to study the validity of co-citation clusters as cognitive units and pertinent social networks in natural science (Mullins et al. 1977), not merely highly visible slices of the literature, as critics charged (Chubin 1976). Lists of highly co-cited documents in several research areas were obtained from Small and Griffith of the ISI. The present study uses ten individual clusters and four combinations of these clusters.

Mullins et al. selected all first authors from the sample documents and also those who co-authored more than one paper, creating author lists from each cluster. This means that the sample is composed of elite, high ranking scientists who appear as first authors, rather than upcoming second or third authors. Two types of sociometric data were collected from authors. First, a questionnaire was sent to the sample of cluster authors, drawing an excellent response rate of over 80 per cent. Second, interviews were held with review-article authors. The information was gathered between May and December, 1975. Original analysis was carried out in 1976 and 1977 (Mullins et al. 1977), and secondary analysis for the present study was carried out in the spring of 1987.

The sample document clusters are not random samples, since they represent the "literary elite" of their respective fields. The papers are recognized by their reference group as significant, possibly influential works. The elite authors of important, co-cited papers were randomly sampled in the original study by Mullins et al. (1977), making the data set viable only for generalizations about select authors in this elite group. The data in this study do not reflect information about scientists generally.

Ten scientific groups are represented in the data set. These are authors of papers in the specialty areas of particle physics (PP: 96 cases), viral genetics (VG: 100 cases), molecular orbital theory (MO: 93 cases), astronomy (AS: 90 cases), nuclear physics (NP: 96 cases), disordered systems (DS: 74 cases) Australian antigen (AA: 86 cases), reverse transcriptase (RT: 82 cases) L Dopa (LD: 46 cases) and molecular collisions (MC: 90 cases). The groups represent a variety of scientific research fronts at the time of the sample. The total number of authors in the sample is 853.

3.2 *VARIABLES FOR ANALYSIS*

The dependent variable in this study is scientific productivity. Scientific productivity is measured in several different ways. The Mullins data set gives indicators of papers published, citations gained, and highly-co-cited papers published. These variables are manipulated to give the measures described below. They represent bibliometric indices of scientific output, the most commonly used measures in evaluation research. It was originally hoped that these indicators would converge upon one central concept (an index of scientific productivity), but they do not, as shown in later analysis.

First, paper publication frequency (SP1) reflects the average scientific output of recognized papers over an eleven year span (1966-1976). It takes the sum of all recognized papers published by a cluster author, regardless of length, quality or contribution to the field, and divides this value by the estimated number of years the scientist was professionally active (after the year of highest degree). It is a limited, partial indicator of scientific productivity.

Second, scientific productivity is measured in terms total citations (SP3) to published papers, standardized by the number of years a scientist was professionally viable, over an eleven year period. This measure is problematic, as discussed earlier, since citations do not necessarily indicate the quality of a publication (e.g. negative or iconic citations). Citations do reflect the impact of a paper, at least (Moed et al. 1984).

Third, the number of highly co-cited papers (SP4) appearing in the paper file of the ISI is an elite, specialized measure of scientific productivity. These papers are taken to represent the number of significant contributions to the specialty made by an author, a good indicator of high quality of output in scientific production. This measure is also standardized by the number of years an author was potentially professionally active, yielding an average annual measure.

The dependent variables are annual averages of the sum total of the scientific product (papers, citations or highly co-cited papers), divided by the estimated number of years an author may have been publishing (YRSPUB). The period under study is from 1966 to 1976, eleven years. The YRSPUB figure is eleven for authors who have been employed since before 1966. For those young authors employed after 1965, YRSPUB is derived by subtracting the year of first job from 1976. This derivation accounts for some of the missing data in the SP variables, since year of first job is missing in some cases of the data set. A base ten logarithmic transformation of the citation count variable is performed in order to moderate the distribution of this highly dispersed measure.

A clear definition of the concept of productivity is important since it has different meanings for different people and on different structural levels. Research must determine

> whether and to what extent the various operational definitions seem to be more or less comparable indicators of a common core variable or whether they may be measure of variables which have different conceptual and substantive import. (Kimberly 1976:586)

Research may find that different indicators converge, yet they measure distinct phenomena. The meaning of scientific productivity depends on the level of scientific production examined, as well as the indicators chosen and measures taken.

3.3 TEST FOR THE CONVERGENCE OF PRODUCTIVITY MEASURES

Several authors have operationalized scientific productivity as a multi-dimensional concept (Andrews ed. 1979, Irvine and Martin 1984b), assuming that simple output measures of publications frequency or abstract measures of "quality" alone are insufficient. The present study recognizes the need for multiple indicators and multi-dimensional concepts, since simple measures do not capture the complex nature of scientific production. For this reason, analysis must test for the convergence of scientific productivity measures.

The question of convergence of dimensions of scientific productivity may be empirically tested by seeing if a single indicator of the different dependent variables is reliable. This problem is solved statistically by computing Cronbach's Alpha for the reliability of a scale. This statistic determines if the dependent measures of scientific productivity converge upon a central, measurable concept. The alpha values are presented in Table 1.

Chronbach's Alpha statistic is a measure of the internal reliability of a multi-item summed index (Bohrnstedt and Knoke 1982:362). Chronbach's Alpha measures the degree to which a number of items are measuring a similar object. The values of Alpha range from zero (no internal consistency) to one (perfect internal consistency). This statistic is an indicator of the convergence of a number of indices of scientific productivity. In the present analysis, the computed standardized item Alpha for all cluster authors combined is very low (.06), well below the required minimum for an acceptable scale or index (.70). This measure remains low at other levels of abstraction. The inter-item correlation between SP1, SP3, and SP4 is also low, with a mean of .05. This indicates that the measures of scientific productivity in this research do not converge upon a core concept, and thus the concept of a single scientific productivity indicator is not used in the analysis.

3.4 INDEPENDENT VARIABLES

This study will consider independent variables of stratification in science, measuring their relation to measures of scientific productivity. The career age of a scientist and prestige of their highest

Table 1. Cronbach's Alpha - Statistics for the Internal Reliability of a Scale for Scientific Productivity

Cluster or Set of Clusters		Alpha Value
1.	All Clusters	.06
2.	Biology Clusters	.04
3.	Chemistry Clusters	.13
4.	Physics Clusters	.07
5.	Australian Antigen Cluster (AA)	.04
6.	Mollecular Collisions Cluster (MC)	.01
7.	Particle Physics Cluster (PP)	.04

degree is correlated with publication productivity (following Hargens et al. 1980), as well "quality" measures of scientific productivity. As described earlier, these variables are consistently used by stratification studies of scientists in organizations. This study will extend their application to co-citation clusters.

The most basic correlate of scientific productivity is career age (Bayer et al. 1966, Bayer and Dutton 1977). Career age is measured in years from the time a researcher earned a Ph.D. or M.D. The success and promotion of elite authors over time may require increasing productivity, both in terms of output quantity and "quality." The shape of the distribution of this variable differs across disciplines and over historical time.

Some authors describe a discipline specific curvilinear relation between chronological age and scientific productivity, peaking when chronological age is in the 40s or 50s (Pelz and Andrews 1967, Andrews 1979). The slowing of productivity growth may be accounted for by researchers taking administrative positions and duties. In this study, career age is measured synchronically by subtracting the year of highest degree from the time of the sampling, 1976.

Theoretically, scientific productivity should correlate with the institutional prestige accorded a scientist's highest degree in the scientific community as a whole. The underlying assumption is that the scientific reward system revolves around the distribution of prestige or recognition by one's peers. It recognizes and rewards the more eminent scientists, enlarging their already sizable reputation (Merton 1968). Crane finds that the prestige accorded a quantitatively productive scientist depends on the prestige accorded their university (Crane 1965). For this reason, institutional prestige is an important variable in the present empirical analysis.

In this study, prestige of highest degree is measured on an ordinal scale according to the rank of academic institution. Authors in the data set are affiliated with "top ten universities", "major state universities", "medical schools" (for biologists only, a relatively low prestige degree), and "other major universities". The variables for first and current job sector (FJOBCAT and JOBCAT) are dummy variables, reduced from the original data into nominal categories, to compare academics and non-academics. Independent variables are not highly intercorrelated, except in the case of the job sector variables, however FJOBCAT is excluded from multiple regression equations in the next chapter.

3.5 STATISTICAL METHODS

This study uses a number of descriptive and inferential statistics to analyze various clusters and sets of clusters in the data set. Initially, frequencies generated from the original Mullins data set allowed construction of the variables for analysis. Frequencies for the second-generation variables are the basis of the descriptive statistics reported in the following chapter. Inferential statistics are also calculated and interpreted for scientific productivity, career age, job sector and prestige variables. Bivariate and multi-variate regression analyses show intercorrelation of the variables and the viability of a general relational model of stratification variables and scientific productivity.

The analysis considers co-citation cluster authors at three levels of abstraction. First, all authors are considered as one, interdisciplinary, elite population. Second, the authors are grouped by scientific discipline. Third, individual clusters are examined when possible. The statistical viability of the authors drops as the population is subdivided, however the groups of authors become more definitely tied into an empirically demonstrable social pattern.

Three methodological steps are taken at each level of analysis. First, the coding of variables and basic descriptive statistics are reported. Second, bivariate correlations for each variable are calculated. Finally, multivariate statistics are computed for those variables strong enough to be used in multiple regression analysis.

4.0 RESULTS OF ANALYSIS

This chapter presents the results of statistical analysis of scientific productivity for co-citation cluster populations. Analysis evaluates the importance of career age and institutional prestige in predicting variation of three scientific productivity indices. Variation in scientific productivity is examined at three levels of abstraction in this chapter. First, ten clusters of scientists are evaluated as a single population. Second, authors in their respective clusters are divided into three scientific disciplines (biology, chemistry, and physics). Third, analysis focuses upon each cluster as a population, an elite reference group in natural science. In this way the attributes of this data set are investigated at general, disciplinary and specialty levels of abstraction, using descriptive and inferential statistical techniques.

4.1 SCIENTIFIC AUTHORS IN CO-CITATION CLUSTERS

The full population of authors in ten co-citation clusters is quantitatively described by the statistics in Table 2. At the time of the original data collection (1976), authors had been professionally viable (having achieved their highest degree) for an average of roughly fourteen years (Mean CARAGE = 14.1). There is quite a bit of variation in this measure of professional age, or experience. The authors had degrees from prestigious institutions, as defined by the original study coding. (Note: The value assigned to medical school was chosen due to it's relatively low prestige for the biologists in the sample). In 1976 the authors were relatively evenly distributed between academic and other areas of work. Co-citation cluster authors published an average of 2.7 papers annually, during the period between 1966 and 1976.

The bivariate correlation matrix for all co-citation cluster is shown in Table 3. Several first-order relationships are noticable, with varying levels of statistical significance due to limits of the data set. First and current job prestige are highly, positively and significantly correlated, as one would expect ($r = .67$). Few other variable pairs show such strong correlation, however. The correlation coefficient for JOBCAT and CATHD is negative, though small, indicating that high prestige graduates may favor academia over other job sectors, in the elite sample.

Career age correlated negatively and moderately only with citations (CARAGE x SP2: $r = -.23$), showing that more experienced authors receive less average attention. This is a notable result for this population, however the relation is not strong. The prestige of highest degree appears to be unrelated to scientific productivity as it is measured in this study. First job prestige correlated

Table 2. Variable Coding and Descriptive Statistics: All Clusters

Independent Variable	Coding	Mean (SD)
1. Career Age (CARAGE)	1976-YRHD	14.1 (9.8)
2. Prestige of Highest Degree (CATHD)	4=Top 18 Univ. 3=Other Major Univ. 2=Medical School 1=Other Univ.	3.3 (1.0)
3. Sector First Job (FJOBCAT)	1=Academic 2=Other	1.4 (.5)
4. Sector Current Job (JOBCAT)	1=Academic 2=Other	1.5 (.5)
Dependent Variable*		
5. Standardized Publication Productivity (SP1)	Interval (0-30) annual papers= SUM (Papers)/yrspub	2.7 (4.5)
6. Standardized Citation Productivity (SP2)	Interval (0-2.7) annual citations=log of SUM (Citations)/yrspub	.24 (.29)
7. Standardized Highly Co-cited Publication Productivity (SP3)	Interval (0-2) annual highly co-cited papers= SUM (HCPs)/yrspub	.16 (.22)

*Scientific Productivity variables (SP1, SP2, SP3) are computed by summing the papers or citations between 1966 and 1976 and dividing by the number of years an author has been publishing (yrspub) during this period.

slightly positively with rougher measures of productivity (FJCAT x SP1: r = .25, FJOBCAT x SP2: r = .24). On the other hand current job prestige mildly correlates with SP3, a more refined measure. This indicates that those authors from academic first jobs are likely to be more avid publishers and garner more citations, and those employed in academia in 1976 are more likely to

Table 3. Bivariate Correlation Matrix - All Clusters

Variable	CARAGE	CATHD	FJOBCAT	JOBCAT	SP1	SP2	SP3
1.CARAGE		.03 (324)	-.07 (163)	-.07 (468)	-.08 (508)	-.23** (508)	-.07 (512)
2.CATHD			-.12 (111)	-.19** (315)	-.04 (327)	.06 (320)	-.09 (327)
3.FJOBCAT				.67** (162)	.25** (163)	.24** (163)	-.05 (163)
4.JOBCAT					.02 (483)	.10 (483)	.23** (506)
5.SP1						-.05 (481)	.20** (554)
6.SP2							.19** (506)
7.SP3							

Key:

Statistics = r Pearson Correlation Coefficient
(n) (Number of Cases)

*p < .05
**p < .01

have highly co-cited papers in the ISI data banks. The correlation matrix in Table 3 also supports the findings from Chronbach's Alpha measures in Table 1. The given productivity measures are not highly intercorrelated in the entire data set.

Table 4 show the results of multivariate analysis for selected variables in all clusters. The low values of Beta in the multivariate regression equations calculated for each combination of dependent and independent variables, and the the low values of the multiple regression coefficient (R-square), show that the model does poorly in explaining variation in productivity measures. Career age appears to have a slightly negative correlation with citations, indicating that senior authors' papers get less attention, but this finding is statistically insignificant. In general, multi-variate modeling does not improve the ability of the independent variables to predict or explain productivity measures. The variation in dependent variables does not follow a pattern which corresponds to variations in independent variables.

In sum, the variables in this analysis show little intercorrelation, when the population is considered as a whole. This is not surprising, since elite authors may come from all backgrounds, and since measures of scientific productivity are not well intercorrelated and highly variable. Consider the standard deviations for dependent variables in Table 2; they are larger than the mean values for all three variables. The diversity in author elites, irrespective of their production, may reflect the diversity of scientific authors and disciplinary contexts. Further specification of the data set is therefore necessary to understand any attributes of the population.

4.2 *COMPARISON OF CLUSTERS IN BIOLOGY, CHEMISTRY AND PHYSICS*

When the sample is divided according to scientific discipline, some variation is revealed in descriptive statistics. Table 5 shows that the physics authors have the highest mean career age, while the chemists have the lowest. The biologists' lower mean prestige of highest degree may be due to the fact that there are medical school graduates in this sub-population, and this category was coded lower due to the relative prestige of a MD for biologists in the sample. It is difficult to code prestige as an interval measure due to this complication, inherited from the variable coding in the original data set. Biologists also appear slightly less likely to work in academia. This may be an artifact of the particular sample clusters. A scan of the Mullins data set shows that hospital positions,

Table 4. Multivariate Regression Statistics: All Clusters

Independent Variable	Dependent Variable SP1	SP2	SP3
1. CARAGE (β)	-.01	-.17*	-.03
2. CATHD (β)	-.06	.02	.11*
3. JOBCAT (β)	-.01	.10	.03
R^2	.01	.04**	.02
N	297	297	297

Key:

Statistics = β (standardized Beta Coefficient for a Multi-Variate Regression Equation)

* $p < .05$
** $p < .01$

classified as non-academic jobs in the current study, may account for this difference. A larger proportion of biologists had worked outside academia, both initially and at the time of the survey, than chemists or physicists.

Biologists also appear to be most productive, at least according to the limited measures in this study. Their mean values are highest on all measures, especially in average publications. Biologists might publish each small advance, whereas physicists must prepare their experiments for years, in some cases, before getting publishable results. This would explain the low publication frequency in physics (mean = 1.6 papers per year). Surely the number of papers is not a measure of their quality, though many use this measure in evaluation research.

Table 5. Variable Coding and Descriptive Statistics for Biology, Chemistry and Physics (Disciplines)

Independent Variable	Coding	Biology Mean (SD) [interval]	Chemistry Mean (SD) [interval]	Physics Mean (SD) [interval]
1. Career Age (CARAGE)	1976-YRHD	14.4 (8.1)	12.3 (9.2)	17 (12.7)
2. Prestige of Highest Degree (CATHD)	4=Top 18 Univ. 3=Other Major Univ. 2=Medical School 1=Other Univ.	2.9 (1.0)	3.5 (0.9)	3.5 (0.8)
3. Sector First Job (FJOBCAT)	1=Academic 2=Other	1.6 (0.5)	1.3 (.48)	1.3 (0.4)
4. Sector Current Job (JOBCAT)	1=Academic 2=Other	1.6 (0.5)	1.4 (.50)	1.4 (0.5)
Dependent Variable*				
5. Standardized Publication Productivity (SP1)	Annual papers= SUM (Papers)/yrspub	3.4 (5.6) [0-30]	2.7 (3.8) [0-30]	1.6 (2.3) [0-12.5]
6. Standardized Citation Productivity (SP2)	Annual citations= log of SUM (Citations) /yrspub	.22 (.20) [0-1.2]	0.3 (.41) [0-2.7]	.21 (.25) [0-2.2]
7. Standardized Highly Co-cited Publication Productivity (SP3)	Annual highly co-cited papers= SUM (HCPs)/yrspub	.20 (.23) [0-2]	0.1 (.22) [0-2]	.14 (.18) [0-1.2]

*Scientific Productivity variables (SP1, SP2, SP3) are computed by summing the papers or citations between 1966 and 1976 and dividing by the number of years an author has been publishing (yrspub) during this period.

Bivariate correlation matrix values for the three disciplines are presented in Tables 6-8. They do not indicate strong variations between disciplines, comparatively. A significant, moderate correlation between publications and category of first job for biologists ($r = .36$) suggests that these authors publish more frequently when they begin their careers outside of academia, especially in comparison to other disciplines. This confirms findings in the descriptive statistics. In all disciplines, especially chemists, career age has a slightly negative relation to citations, suggesting that experienced authors receive slightly less reference, and that younger authors have a larger average impact. This finding is statistically significant in all cases.

When multivariate regression models are calculated for disciplinary sets of clusters, the results are weak and insignificant on the whole. Chemistry could be considered a slight exception, especially in the case of citations (SP2). In predicting citation frequency per year, career age significantly explains a moderate portion of the variance (Beta = .32). This indicates that a chemistry author's experience contributes to the 16 per cent of total variance explained in citation frequency (R square = .16). However the explanatory strength of the model used in this study remains poor, judging from the values of the multiple correlation coefficient across disciplines. The chemistry population is slightly more amenable to prediction of productivity from prestige and experience, however none of the multiple regression equations which may be generated from the statistics in Table 9 would be strong evidence for a theory that productivity differences are related to social stratification variables in a linear model.

The population is neither a random nor representative sample of any particular scientific discipline, making generalization difficult. There are also small number and missing data problems in the data set, weakening the grounds for fair comparison of disciplines. Finally, it is evident that some indicators are better suited for one discipline than another. For example, first authorship in experimental particle physics is often based solely on alphabetical order, and many papers are "written" by large groups. In this case a publication doesn't have the same weight as in molecular biology, where a small group lead by a senior scientist may value first authorship. It is therefore hazardous to compare performance indicators across disciplines, due to the varying reliability of these measures.

Table 6. **Bivariate Correlation Matrix - Biology Clusters**

Variable	CARAGE	CATHD	FJOBCAT	JOBCAT	SP1	SP2	SP3
1.CARAGE		.01 (132)	-.02 (59)	.01 (215)	-.07 (293)	-.19** (234)	-.07 (235)
2.CATHD			-.13 (32)	-.21 (132)	-.07 (137)	-.14 (132)	-.13 (134)
3.FJOBCAT				.79** (58)	.36** (59)	.16 (59)	-.08 (59)
4.JOBCAT					.06 (224)	.05 (214)	-.07 (221)
5.SP1						.23 (234)	.20 (251)
6.SP2							.03 (234)
7.SP3							

Key:

Statistics = r Pearson Correlation Coefficient
(n) (Number of Cases)

*p < .05
**p < .01

4.3 ANALYSIS OF INDIVIDUAL AUTHOR CLUSTERS

The examination of co-citation cluster author productivity, in contrast to the productivity of administrative reference groups, is the final goal of empirical research. The examination of co-citation clusters is possible when the population is divided into its original ten sets of research writers. The

Table 7. **Bivariate Correlation Matrix - Chemistry Clusters**

Variable	CARAGE	CATHD	FJOBCAT	JOBCAT	SP1	SP2	SP3
1.CARAGE		.11 (106)	-.08 (62)	-.18 (138)	-.12 (147)	-.27** (146)	-.13 (149)
2.CATHD			.08 (45)	.00 (99)	.17 (105)	.17 (105)	.06 (106)
3.FJOBCAT				.65* (62)	.09 (62)	.41 (62)	-.04 (62)
4.JOBCAT					-.08 (141)	.24** (137)	.09 (142)
5.SP1						.35** (146)	.21** (159)
6.SP2							.46** (146)
7.SP3							

Key:

Statistics = r Pearson Correlation Coefficient
(n) (Number of Cases)

*p < .05
**p < .01

ten co-citation clusters in this study are from a range of specialty areas, as described earlier. Three of the ten clusters are examined below, one specialty area from each discipline.

Descriptive statistics presented in Table 10 summarize the clusters of authors in australian antigen (AA), molecular collisions (MC) and particle physics (PP) research specialties. Their numbers are small, and there is limited variation aming and between these groups. Particle physicists are the most professionally experienced (mean CARAGE = 17.8 years), followed by the AA biologists (14.8) and the younger MC chemists (10.2). The biologists again appear less prestigious, partly due to the variable coding of medical schools. Biologists are also more likely to be employed outside of academia. These same AA authors are the most frequent publishers but the least often cited.

Table 8. Bivariate Correlation Matrix - Physics Clusters

Variable	CARAGE	CATHD	FJOBCAT	JOBCAT	SP1	SP2	SP3
1.CARAGE		.10 (86)	-.20 (42)	-.11 (115)	-.07 (127)	-.21* (126)	-.11 (128)
2.CATHD			-.41 (34)	-.19 (84)	.12 (85)	-.11 (85)	.14 (87)
3.FJOBCAT				.50** (42)	-.21 (42)	-.05 (42)	-.23 (42)
4.JOBCAT					-.20* (118)	.00 (112)	-.14 (118)
5.SP1						.24** (126)	.08 (145)
6.SP2							.05 (126)
7.SP3							

Key:

Statistics = r Pearson Correlation Coefficient
(n) (Number of Cases)

*p < .05
**p < .01

The MC authors rarely have a highly cited paper. This indicates that AA authors publish liberally and cite less frequently (inside their ranks), and the MC chemists are not referring to a homogeneous set of works.

Bivariate correlations in Tables 11-13 show the intercorrelation of variables for the three representative cluster populations. These figures generally lack statistical significance. The data set information available could easily produce accidental relationships, however these tables are presented to show what clusters themselves look like in terms of some interesting variables. There are two potentially interesting relationships. First, in the AA table, CATHD x SP3 shows a high, positive correlation for 28 cases. This is surprising, indicating that some less prestigiously educated biol-

Table 9. Multivariate Regression Statistics for Biology, Chemistry and Physics (Disciplines)

	Dependent Variable								
	Biology			Chemistry			Physics		
Independent Variable	SP1	SP2	SP3	SP1	SP2	SP3	SP1	SP2	SP3
1. CARAGE (β)	-.03	-.12	-.02	.08	.32**	-.21*	-.11	-.22*	-.11
2. CATHD (β)	-.07	-.12	-.12	.20*	.16*	.06	-.08	-.12	.18
3. JOBCAT (β)	.04	-.07	.08	-.21*	-.12	-.14	-.14	-.06	-.03
R^2	.09	.03	.03	.08*	.16**	.05	.04	.06	.04
N	122	122	122	95	95	95	80	80	80

Key:

Statistic = β (Standardized Beta Coefficient for a Multivariate Re gression Equation)

* $p < .05$
** $p < .01$

ogists produce more influential papers (or at least make bigger impacts with their publications). The results suggest that higher institutional prestige in the training of AA biologists does not imply quality of work. Second, the MC chemists in non-academic positions are likely to have higher citation rates. The academics are not as widely recognized in MC chemistry. These findings may be particular to the data set, however. The absolute zero correlation in the table for PP shows that the relations between variables at this level of abstraction may not exist, since the numbers are not always strong enough to support regression analysis.

In general, the measures of scientific productivity used in this study are not well explained by stratification variables of career age and institutional prestige. Elite scientific authors in clusters are

Table 10. Variable Coding and Descriptive Statistics for AA, MC and PP (Individual Clusters)

Independent Variable	Coding	AA Cluster Mean (SD) [interval]	MC Cluster Mean (SD) [interval]	PP Cluster Mean (SD) [interval]
1Career Age (CARAGE)	1976-YRHD	14.8 (7.4)	10.2 (8.6)	17.8 (14.6)
2Prestige of Highest Degree (CATHD)	4=Top 18 Univ. 3=Other Major Univ. 2=Medical School 1=Other Univ.	2.5 (0.8)	3.6 (.78)	3.8 (0.4)
3Sector First Job (FJOBCAT)	1=Academic 2=Other	1.8 (0.4)	1.2 (.44)	1.3 (0.5)
4Sector Current Job (JOBCAT)	1=Academic 2=Other	1.7 (0.5)	1.3 (.47)	1.3 (0.5)
Dependent Variable*				
5. Standardized Publication Productivity (SP1)	Annual papers = SUM (Papers)/yrspub	4.0 (5.5) [0-29]	2.7 (3.5) [0-17]	2.2 (2.3) [0-9.8]
6. Standardized Citation Productivity (SP2)	Annual citations = log of SUM (Citations)/ yrspub	.22 (.24) [0-1.2]	.27 (.36) [0-2.0]	.25 (.14) [0-0.6]
7. Standardized Highly Co-cited Publication Productivity (SP3)	Annual highly co-cited papers = SUM (HCPs)/yrspub	.25 (.23) [0-0.9]	.04 (.17) [0-1.2]	.27 (.23) [0-1.2]

*Scientific Productivity variables (SP1, SP2, SP3) are computed by summing the papers or citations between 1966 and 1976 and dividing by the number of years an author has been publishing (yrspub) during this period.

diverse, however there is no convincing evidence that differences between authors correspond to differences in the outputs of scientific production.

The multi-variate statistics in Table 14 are significant in two cases. For the AA cluster, including CARAGE, CATHD and JOBCAT in a regression equation yields a regression coefficient of R =

Table 11. Bivariate Correlation Matrix - AA Cluster

Variable	CARAGE	CATHD	FJOBCAT	JOBCAT	SP1	SP2	SP3
1.CARAGE		-.11 (28)	.00 (5)	-.10 (39)	-.14 (51)	-.21 (51)	-.15 (51)
2.CATHD			-1.0 (2)	.32 (22)	-.06 (28)	-.10 (28)	-.51 (28)
3.FJOBCAT				.61 (5)	.31 (5)	.04 (5)	.32 (5)
4.JOBCAT					.18 (39)	-.01 (39)	.18 (39)
5.SP1						.05 (51)	.26 (51)
6.SP2							.20 (51)
7.SP3							

Key:

Statistics = r Pearson Correlation Coefficient
(n) (Number of Cases)

*$p < .05$
**$p < .01$

.44. In 22 cases, 44 per cent of the variation in SP3 is explained by the age and prestige variables, most notably CATHD. This means that prestige of AA authors is a major contributor to variation in their rate of publication of highly recognized papers, which is not surprising. This result is not replicated in other clusters however, nor does it appear in the more general populations. Such rare findings indicate that scientific authors produce in different ways, specific to their specialty.

A second notable result is that 25 percent of the variation in MC citation frequency is explained by the stratification variables used in analysis. This is significant for the job sector of these chemists. Non-academic publishers are quite well referenced. Academic prestige may have little bearing in this case, since non-academics show a higher citation rate. In some specialties, recognition and

Table 12. Bivariate Correlation Matrix - MC Cluster

Variable	CARAGE	CATHD	FJOBCAT	JOBCAT	SP1	SP2	SP3
1.CARAGE		.04 (49)	-.24 (32)	-.29 (56)	-.03 (62)	-.28 (61)	-.07 (64)
2.CATHD			-.14 (24)	-.08 (44)	.11 (48)	.24 (47)	.12 (50)
3.FJOBCAT				.70 (32)	.27 (32)	.46** (32)	-.19 (32)
4.JOBCAT					.06 (57)	.29 (56)	-.13 (60)
5.SP1						.11 (61)	.11 (71)
6.SP2							.04 (61)
7.SP3							

Key:

Statistics = r Pearson Correlation Coefficient
(n) (Number of Cases)

*p < .05
**p < .01

reference may have more to do with professional affiliation or job sector than with prestige of highest degree. This result is cluster specific however, and shows that there are differences between specialties.

To summarize empirical results, the sample of cluster authors is somewhat heterogeneous, yet there is no strong statistical explanation for the diversity uncovered in the data set. In some sub-populations, it is evident that younger authors are more productive, in accordance with earlier analysis of the biologists in the current data set (Hargens et al 1980). Biologists, working more frequently outside of academia appear most productive, and chemists' productivity is best explained by demographic measures. Notably, younger chemists gather the most average annual citations.

Table 13. Bivariate Correlation Matrix - PP Cluster

Variable	CARAGE	CATHD	FJOBCAT	JOBCAT	SP1	SP2	SP3
1.CARAGE		-.08 (39)	-.26 (17)	-.20 (51)	.00 (55)	-.10 (55)	-.03 (55)
2.CATHD			-.41 (14)	-.16 (40)	-.17 (40)	-.05 (39)	-.10 (39)
3.FJOBCAT				-.43 (17)	-.28 (17)	-.15 (17)	-.37 (17)
4.JOBCAT					-.15 (53)	.11 (51)	-.13 (51)
5.SP1						.24* (55)	.00 (55)
6.SP2							.05 (55)
7.SP3							

Key:

Statistics = r Pearson Correlation Coefficient
(n) (Number of Cases)

*p < .05
**p < .01

The data is thin on individual specialty clusters, the true unit of this analysis. That data which may be analyzed shows that stratification variables of career age and institutional prestige do not account for variation in performance measures. This is true in linear bivariate and multivariate regression models. On the whole, scientific productivity is not found to be strongly explained by the position of an elite author in a hierarchy of experience or by the institutional prestige of their highest degree.

Table 14. Multivariate Regression Statistics for AA, MC and PP Clusters

	Dependent Variable								
	AA Cluster			MC Cluster			PP Cluster		
Independent Variable	SP1	SP2	SP3	SP1	SP2	SP3	SP1	SP2	SP3
1. CARAGE (β)	.29	-.07	.29	.05	-.13	-.16	-.08	.01	.00
2. CATHD (β)	-.22	.17	.57	.07	.25	.13	-.16	.04	.10
3. JOBCAT (β)	.44	-.20	.03	-.16	.39**	-.13	-.01	-.01	.14
R^2	.26	.05	.44*	.04	.25**	.04	.03	.01	.03
N	22	22	22	43	43	43	39	39	39

Key:

Statistic = β (Standardized Beta Coefficient for a Multivariate Re gression Equation)

* $p < .05$
** $p < .01$

5.0 CONCLUSION

This study examines scientific research productivity among members of reference groups in natural science through the empirical analysis of authors in co-citation clusters. Scientific authors are examined at three levels of abstraction. Analyses view natural scientific authorial elites as a general population, in disciplinary populations, and in their original specialties or cluster populations. Descriptive statistics show that groups of authors are internally heterogeneous, and that group characteristics vary slightly by discipline and specialty. In linear regression analysis, stratification variables poorly explain measures of scientific productivity, in most models and in most cases. Scientific publications by elite scientific authors and their impact cannot be simply and linearly explained by career age, job sector and institutional prestige of highest degree.

This concluding chapter will begin with a review of the major findings of analysis, in general and at each level of abstraction. Some implications of research will show how the findings generalize to larger issues in the sociology of scientific production. A final section will give some suggestions for future analysis which follow from the results of this research.

5.1 MAJOR FINDINGS OF ANALYSIS

This study examines the scope and impact of knowledge production among highly recognized authors in the natural sciences. An elite, central, interdisciplinary sample of research writers is examined to see the relationship between social stratification and scientific productivity variables. The findings show that career age, job sector and institutional prestige of highest degree are poor explanatory variables in predicting variation in average annual paper publication, average annual citations gained, and highly co-cited papers published. The findings are roughly consistent at three levels of analysis. Few strong statistical values are produced by analysis of the sample. This implies that variation in scientific author elites cannot be simply explained by the experience and affiliation of the author.

Scientific productivity is operationalized in terms of paper publication frequency, citation frequency and highly co-cited paper frequency. These bibliometric indicators are measured and standardized over several years for co-citation cluster authors. They do not converge upon a core concept, according to a statistical measure of reliability. Divergent measures of scientific productivity indicate that it is not a singular, monotonic variable.

The complexity of these relationships takes root in the complexity of measuring scientific productivity. Since indices of scientific productivity do not converge in this study, and rarely converge in others (Irvine and Martin 1984b:202), it is difficult to use the concept of scientific productivity as a single dependent variable in analysis. Theoretically, scientific productivity has different definitions for different researchers, depending upon the unit of analysis and the scope of research. A review considering simply publication productivity (Fox 1983) ignores the fact that scientific output consists of more than publications. In addition, input variables should be considered, in order to formulate accurate performance measures, ratios of input and output. Publications gather citations and the value of the publication changes over time, with respect to the specialty or reference group in the scientific community.

At the most general level of abstraction, scientific authors in clusters are active publishers who get less references than publications. Academics are more likely to have gained a degree from a prestigious university. These authors have a wide range of professional experience, however the variation in experience has little relation to variation in bibliometric productivity. The same may be said of prestige and job sector. Co-citation cluster authors appear idiosyncratic, in general.

At the level of natural science disciplines, biologists stand out as the most frequent paper publishers, above chemists and physicists respectivly. This may be explained by differences in publication practices and experimental lifetimes. Chemists and physicists in the sample are more in the academic sector. Independent measures of social stratification continue to lack explanatory power at this level. Only chemists' citation frequency is minimally predictable, largely by career age.

At the level of specialties, the origin of the clusters, the variation between disciplines is replicated. Biologists in australian antigen research are the most frequent publishers, largely in non-academic jobs. The variation in measures of scientific productivity is significantly correlated with independent variables only in rare cases. Multivariate modeling helps to explain a small fraction of scientific productivity variation in molecular chemistry, where being an academic is a contributing factor in explaining citation variation. This relation again reflects disciplinary findings.

At all levels of analysis examined, with minimally significant exceptions, variables of career age and institutional prestige of highest degree do not explain variation in scientific productivity, using a linear model. This is consistent with findings on career age (Pelz and Andrews 1966, Bayer and Dutton 1977), which require complex functions to describe the relation between career age and publication productivity, and still find poor fits and variation between specific populations. It is less consistent with earlier studies of institutional prestige, which reach a variety of different conclusions using different research techniques and hypothetical models.

The findings concerning institutional prestige suggest that prestige of highest degree is not significant to productivity in science, regardless of discipline, specialty or job category. If it is the case that the importance of institutional prestige increases over time during the career (Long 1978), then the prestige of first job and current job should become progressively more important with career age. This theory cannot be tested with a cross-sectional model and the data set at hand. The results do extend an earlier finding from authors in general to the authorial elites; there are only slight differences in the correlates of institutional prestige across disciplines (Hagstrom 1971). However the present research finds these correlations to be consistently low for cluster authors, not high, as is the case in Hagstrom's study.

The cognitively elite reference groups represented by paper co-citation clusters in scientific specialties are heterogeneous. Rather than old, prestigious icons of intellectual achievement, the authors are found to be dispersed over a wide range of demographic categories. This confirms earlier work which finds that central author elites in biological sciences are younger, rather than older than the norm for a general sample in biology (Hargens et al 1980).

Different clusters, specialties and employment sectors show some significant differences in scientific productivity, verifying for co-citation clusters certain findings in the literature (Hagstrom 1965; Allison and Stewart 1974). This finding reflects the different publishing and referencing patterns in different sciences, and the variation in the time and scope of experimental paper across discipline. Further research is necessary to specify the reasons for these differences.

In general, the performance of elite authors in science, is not strongly explained by linear or economic models. The variation in productive processes, environments, and types of inputs and outputs compounds problems of analysis. For co-citation cluster authors in this study, there are no simple causal patterns between experience and prestige of highest degree variables, and outputs from natural scientific production. This finding may be generalized across disciplines and levels of analysis.

In summary, empirical analysis of authors in ten co-citation clusters finds that authors in a central, cognitive elite, identified by the prominence of their papers, are heterogeneous reference groups. In co-citation cluster author populations studied, degree of scientific productivity, institutional prestige rankings and career age vary widely, yet they are not highly intercorrelated. Variations in stratification characteristics does not explain variation in performance, regardless of specialty or discipline. Generally, scientific productivity does not correspond to unique characteristics of social stratification among co-citation cluster authors.

5.2 *IMPLICATIONS OF RESEARCH*

Several implications can be drawn from the research findings in this study. First, co-citation cluster authors, shown to be somewhat different from a general sample of authors in biology (Hargens et al 1980), are more comparable with general populations in terms of how author performance may be explained. Career age does not explain performance variables in a linear model, as is the case with studies of general populations in most scientific disciplines (Bayer and Dutton 1977). The import of institutional prestige of highest degree is more difficult to compare, since the literature in this respect is diverse. The cluster authors in this study come from prestigious institutions, not surprisingly, but the relative prestige does not affect the average magnitude or "quality" of their output. In this respect one can consider cluster authors to be like the majority of researchers. Prestige may be a result, rather than a cause of good performance. This hypothesis remains to be tested for author elites.

Second, the variability of scientific production varies marginally across disciplines for cluster authors, but this variation is not clearly a result of any characteristic of the author. Their contributions may be few and strong, or they may be young and not in a prestigious institution, and they still may appear in central areas of a specialty. The resources potentially gained through experience and prestige of highest degree are not factors in explaining the quantity or bibliometric quality of authors in the thick of scientific research. The quality of the work itself inevitably could affect it's impact and an author's publishing frequency, regardless of the author's experience or institutional afilliation. The productivity of authors in a variety of reference groups studied eludes simple, linear explanation.

Third, measures of scientific productivity are complex and need further specification. Paper publication frequency, citation frequency, and publication of highly co-cited paper frequency are all interesting but not intercorrelated indicators. More indicators need to be tapped, and additional measures specified to distinct research areas. The performance criteria of central authors in all disciplines must be specified carefully if they are to be even potentially explained by stratification variables. Inputs and outputs of work processes might be considered in a ratio measure of output per unit input, if carefully specified. However there is no clear relation between quality and quantity of research output, in principle and as shown by empirical analysis.

Fourth, scientistific elites are quite heterogeneous. There is no demographic formula for entrance into the cognitive elite of co-citation clusters (Hargens et al 1980), and there is no formula for predicting the performance of an author in the elite. Production of interesting new knowledge remains a process which is difficult to model sociologically. There is as much variation in the elite which cannot be explained as there is in the general population. Reference groups are no simpler than membership groups.

The natural science authors in the thick of knowledge production are not only those elders with high prestige degrees, churning out important documents and garnering citations. In order to understand the processes by which knowledge is made by central figures in published research, one must consider numerous cognitive factors, as well as the specificity of research contexts. Scientific production could take as many forms as the products of science, a diversity which may ultimately benefit both the scientist and the user of new knowledge.

5.3 FUTURE ANALYSIS OF KNOWLEDGE PRODUCTION

The results of this study suggest a number of considerations and directions for future research. In terms of developing a model for knowledge production, this research has shown that strict linear models have limitations. More complex functions must be considered. Production of knowledge by central authors does not fit industrial, mechanical, or regression models. Outputs have different meanings and few statistical correlates across disciplines. Models of knowledge production should specify a limited population at first, then chose indicators relevant to that group. Comparison across disciplines or even specialties becomes hazardous, since prestige and performance mean different things to different populations. Indices of publication, such as first authorship, have different meanings between and even among specialties. To model structure of science, "black boxing" the production process is dangerous.

In studying social forms in scientific production, one must either accept the haziness of measurement in a large population or the statistical weaknesses of a smaller population with a higher resolution in operationalization. Entire disciplines may not be commensurable, and the validity of measures may fail across disciplinary boundaries. The same can be said for specialty reference groups. At the same time, the numbers in commensurable social units may be too small for strong statistical methods.

If one does model stratification variables against production variables, there are two problematic issues. First, what will the relation look like, and are populations with a similar productive process large enough to yield significant results? Second, is there any sense in which one can fit a temporal model (assumed in multiple regression analysis) onto a productive and reward process which is certainly cyclical and/or reciprocal? Since science is not involved in a mechanistic production process (at least in terms of published knowledge), are communities of researchers amenable to other large-scale statistical tools? These questions remain a challenge to research which considers scientific production among stratified authors in structured fields of inquiry.

Future studies must consider a broad range of dependent variables to indicate scientific productivity, and their possible convergence within sub-populations. Measures of input, such as grant dollars on a large scale or computer (CPU) time on a small scale, could be used to compliment bibliometric measures with work performance indicators. Complimentary measures of input and output could be standardized over time and/or in terms of contextual measures, such as group size or institutional overhead. As performance measures became more complex, qualitative research would be necessary to insure the subjective validity of each measure for the sub-populations under study. Different questions and indicators would apply to various social units.

The results of laboratory studies, using participant-observation in scientific institutions or departments, may insure that productivity research asks viable, relevant questions, to construct better indicators. The social surface of productivity studies must remain conscious of the very deep cognitive structure supporting natural scientific endeavors. As others have argued, both cognitive and social structure are important to understanding science (Chubin 1980). Sociological accuracy requires that indicators of performance be evaluated through direct contact with the subjects and subject of research, organized to evaluate the indicators in a systematic fashion. Only through experience or direct contact with scientific practitioners can the value of bibliometrics and work performance measures be evaluated.

Research should allow that the social production of science actually follows multiple patterns of knowledge construction. A single model can rarely be valid across social boundaries, with accuracy. Sociology can provide different, correct explanations for scientific production in numerous scientific contexts. Science takes place within multiple organizational forms, and therefore a variety of models and methodologies remain necessary to understand and explain the social processes of knowledge production.

Research need not remain restricted solely to sociological traditions which have grown from the pioneering work of Merton or Kuhn. Many literatures add to the understanding of knowledge production, enriching and complicating the field of science studies. From microscopic analyses of laboratory life to comparative studies of national laboratories, sociologists must continue to probe the complexities of scientific work. The challenges brought by constructive criticism should enhance, not deter, future studies. Science remains the successful product of social groups which accept and cultivate the growth of knowledge.

This study shows that the productivity of co-citation cluster authors, as measured by bibliometric indicators of publication and citation frequency, may not be explained by stratification of scientists, in a linear model. Career age, prestige of highest degree and job sector are important variables in describing scientists, but not relevant to explanation of variation in the products of scientific work. Further research must involve complex indicators of performance, additional independent variables, and calibration of indices with qualitative research. Understanding the social production of scientific knowledge remains a challenging problem for social science.

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Education

M.S. - 1988 Virginia Tech
Major: Sociology
Thesis: "Scientific Productivity in Co-citation Clusters"

B.A. - 1984 Wesleyan University
Majors: Anthropology, Science in Society
Honors Thesis: "A Culture of Science: An Ethnography of a Plasma Physics Research Group"

Awards and Honorary Societies

Selected Graduate Representative, University EO/AA Committee (1986)

Treasurer, Alpha Kappa Delta Honor Society - Virginia Tech (1986)

Member Sigma Xi Scientific Honor Society - Wesleyan University (1984)

Cushing Award for Excellence in Anthropology - Wesleyan University (1984)

Student Fellow, Wesleyan Center for the Humanities (1983)

Research Experience

Research Assistant in Sociology, European Center for Nuclear Physics (CERN), 1987-present.

Graduate Assistant, Virginia Tech Sociology Department (1986-87)

Thesis Research, M.S. in Sociology, Virginia Tech (1986-87)

Thesis Research, B.A. in Anthropology, Wesleyan University (1983-84)

Fieldwork, Massachusetts Institute of Technology, Plasma Fusion Center (1983)

Teaching Experience

Guest Lecturer, Virginia Tech, Introductory Sociology and Social Problems (1986-87)

ESL instructor, Jewish Vocational Service, Boston MA (1985)

English Instructor, International House Language School, Budapest Hungary (1984)

Physical Education Instructor, Saint Mary's School, Middletown CT (1982-83)

Paper Presentations and Meetings

Attended Social Studies of Science Meetings (1985-86)

Delivered paper "A Culture of Science" to Sigma Xi Research Colloquium (1983)

Respondent, Wesleyan Center for the Humanities Colloquium (1983)

Language Skills

French, Spanish, Hungarian, BASIC.

User of IBM VM, Micro and Macro-computer word processing languages