Impacts of an Interdisciplinary Research Center on Participant Publication and Collaboration Activities

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Dedication

I dedicate this work to my husband and best friend, Todd, whose selfless support, understanding, and encouragement has been a great source of strength. I also dedicate this work to my sweet children Grayson and Lila. I started this journey for me, but I ended it for you—never, never, never give up.

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Abstract

Interdisciplinary research centers are typically presented as a means for exploiting opportunities in science where the complexity of the research problem calls for sustained interaction among multiple disciplines. This study analyzed the effects of an interdisciplinary research center (NIMBioS) on the publication and collaboration behaviors of faculty affiliated with the center. The study also sought to determine what factors contributed to these effects for participants whose publication and collaboration behaviors were changed the most after affiliation.

The study employed a mixed-method case study approach, using quantitative bibliometric data along with qualitative data collected from interviews. Publication data for each participant in the study was collected from Web of Science (WOS) and analyzed by year against several demographic control variables to understand what effect affiliation with NIMBioS had on publication behaviors of participants. In addition to bibliometrics, a selection of study participants who demonstrated the most change in publication and collaboration behaviors since their affiliation with NIMBioS were interviewed to determine (a) what benefits (if any) participants felt they achieved as a result of participating in their working group, and (b) what factors (if any) participants felt may have contributed to the impact of NIMBioS affiliation on their publication and collaboration behavior.

Results of the study indicate that affiliation with a NIMBioS working group has a significant positive effect on participant collaboration activities (i.e. number of co-authors, number of international co-authors, number of cross-institutional co-authors), and a moderate effect on publication activities (i.e. publishing in new fields). Qualitative analysis of interdisciplinarity showed a shift in publication WOS subject categories (SCs) toward mathematical fields. Factors contributing to success cited by interviewees included organized leadership, a positive atmosphere, breaking into sub-groups, and the ability to collaborate with researchers with whom they would not have interacted outside of the group.

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CHAPTER 1

INTRODUCTION

This chapter provides an overview of the study, beginning with the prevalence and importance of interdisciplinary research (IDR) in today's academic climate. It defines IDR, and situates the current project's purpose, importance, and context within this growing phenomenon. Research questions, assumptions, and limitations of the project are outlined, as well as the study methodology, a brief definition of key terms, and the organization of the study.

Prevalence of Interdisciplinary Research

Interdisciplinary scientific collaboration has been on the rise in recent decades (Borner et al., 2010; Falk-Krzesinski et al., 2011; Stokols, Misra, Moser, Hall, & Taylor, 2008; Trochim, Marcus, Masse, Moser, & Weld, 2008; Wagner et al., 2011). The rapid expansion of scientific and technical knowledge has caused increased specialization within scientific fields, and new complex questions arising from this knowledge must be addressed simultaneously through collaboration among specialists from multiple fields (National Academy of Sciences, 2004). A study by Braun and Schubert (2003) showed that the prevalence of the terms 'interdisciplinary' and 'multidisciplinary' in titles of papers covered by the Thomson Institute for Scientific Information's (ISI) Science Citation Index (SCI) database grew exponentially from 1980 to 1999, doubling in a span of seven years. Though not a direct indicator of IDR, this finding indicates that interest in the phenomenon has increased significantly in recent years. IDR makes it possible to create novel solutions to address new or existing research questions that are beyond the scope of a single discipline or field of research (National Academy of Sciences, 2004). The benefits of IDR include enhanced productivity, enhanced inquiry, and improved problem-solving (Aboelela et al., 2007; Melin, 2000).

Although there is agreement that scientists are reaching across disciplines to collaborate on research, there is no single agreed-upon definition of IDR (Porter, Roessner, & Heberger, 2008). A commonly used taxonomy of cross-disciplinary research was introduced by Rosenfield (1992), who proposed a classification scheme that includes three types of cross-disciplinary collaboration: multidisciplinary (researchers look at a problem in parallel or sequentially from the perspectives of their own fields); interdisciplinary (researchers work together on a problem, but still from the perspectives of their own disciplines); and transdisciplinary (researchers work synergistically using a shared conceptual theory and approach derived from all discipline areas involved). Although these categorizations are in the literature, there is still no consensus regarding specific methodologies that would allow concrete classification of research into one or the other of these categories (Bordons, Morillo, & Gomez, 2004; Porter et al., 2008). Several studies have noted that the term ‘interdisciplinary’ is widely used to mean research spanning a variety of disciplines or research fields, and thus the term encompasses all three cross-disciplinary categories of research (Bordons et al., 2004; Huutoniemi, Klein, Bruun, & Hukkinen, 2010; Metzger & Zare, 1999; Rafols & Meyer, 2010). Accordingly, the present study uses the term ‘interdisciplinary’ to describe research that falls into any of the three categories described above.

Evidence of increased commitment to IDR can be seen across government and private sector funding organizations alike. The U.S. National Institutes of Health (NIH) roadmap for Medical Research includes initiatives that clearly recognize the importance of IDR as a catalyst for scientific discovery (Zerhouni, 2003). Examples of NIH initiatives that emphasize IDR include the National Cancer Institute's Transdisciplinary Tobacco Use Research Centers, Transdisciplinary Research on Energetics, and the Centers for Population Health and Health Disparities (Borner et al., 2010). The National Science Foundation (NSF) reports that the agency "has long recognized the value of interdisciplinary research in pushing fields forward and accelerating scientific discovery" (Paletz, Smith-Doerr, & Vardi, 2010, para.1). NSF actively promotes IDR through several initiatives, including solicited interdisciplinary programs such as Cyber-enabled Discovery and Innovation, Collaboration in Mathematical Geosciences, and Macrosystems Biology; center competitions, such as Materials Research and Engineering and Science and Technology Centers; unsolicited interdisciplinary proposals; education and training programs; and through workshops and other forums (National Science Foundation, 2011b).

In addition to government funding agencies, private organizations also support IDR. For example, the Robert Wood Johnson foundation reports that it is "helping to develop a new transdisciplinary field of active living researchers" through its Active Living Research program to prevent childhood obesity and support active communities (Robert Wood Johnson Foundation, 2011, para. 1). The William T. Grant Foundation indicates that an interdisciplinary approach is characteristic of much of the research that the foundation has funded (William T. Grant Foundation, 2010). Additionally, the MacArthur foundation “promotes intellectual collaboration rather than competition, and interdisciplinary approaches rather than monodisicplinary concentration” (Kahn, 1992, p. 1).

Interdisciplinary Research Centers

A significant vehicle for facilitating IDR is the research center (Tash, 2006). According to the Research Centers and Services Directory ("Research centers and services directory," 2011), there are more than 15,900 university-based and other nonprofit research centers in the United States and Canada and more than 37,000 worldwide. According to Tash (2006), research centers are creating a new model for who performs science, as well as the impacts and purposes of the research. Research centers “can substantially enhance a university's capability to attract external funding, provide opportunities for interdisciplinary collaboration among faculty, and provide considerable visibility and prestige in a defined area of study for the research university” (Stahler & Tash, 1994, p. 540).

While research centers have been in existence for quite some time, the importance of research centers has grown over the last several decades, as evidenced by the increase in funding for these ventures from major federal agencies such as the NIH and the NSF (Coburn, 1995; Gray, 2008; Tash, 2006). In FY 2011, NSF funded 107 research centers with a total of almost $300,000,000 (National Science Foundation, 2012). Because of the large amount of resources invested in IDR centers, a need exists to understand these centers from the perspective of what is working, and what is not. There is also a need to determine how the outcomes of the centers are being achieved (Tash, 2006).

Statement of the Problem

Evaluation of federally-funded research has gained much attention since the passing of the Office of Management and Budget's (OMB) Government Performance and Results Act (GPRA) in 1993, and the subsequent GPRA Modernization Act of 2010. GPRA requires federal agencies to quarterly report on the accomplishments of their funded projects within specific guidelines provided in the Program Assessment Rating Tool (PART) (Office of Management and Budget, 1993, 2010). This legislation was part of a larger reform effort aimed at creating a more effective and efficient government during a time when annual federal budget deficits were exceeding $200 billion. The large national debt, the need for a balanced budget, and the increasing cost of entitlement programs expanded pressure on the allocation of limited financial resources available for many government activities, including funding for scientific research (Office of Postsecondary Education, 1998). Although GPRA does not directly address organizations that receive grants from federal agencies, it is imperative that recipients of federal funding for research, including research centers, follow the guidelines of GPRA to ensure that grantees are providing their funding agencies with the necessary information to meet the expectations of Congress under the act (Tash, 2006).

IDR center evaluations are used for accountability, to improve center efficiency, and to assess outputs, outcomes, cost-benefits, and impacts (Tash, 2006). Deciding who, what, and when to evaluate can be problematic, however, due to the complex nature of centers' research portfolios and missions and the multiple internal and external stakeholder groups that need to be addressed (Gray, 2008). Evaluators still know relatively little about how to evaluate the progress and effectiveness of large IDR centers (Trochim et al., 2008). Evaluation approaches could include efficiency, implementation, or impact studies; incidence, amount, and quality of IDR; cost-benefit analyses; studies of staff and client satisfaction; or studies of the social processes of team science (Tash, 2006).

Because of the interdisciplinary focus of many centers, one approach to evaluating IDR centers is to examine the effect of affiliation with the center on the interdisciplinary publication and collaboration activities of its participants. It is of major interest to funding agencies to know to what extent center participants are collaborating across disciplines to tackle research problems (Norman, Best, Mortimer, Huerta, & Buchan, 2011; Stokols, Misra, et al., 2008). However, this type of evaluation is not without its own complexities. According to Klein (2008), evaluation of IDR is "shaped by multiples: multiple actors making multiple decisions in varied organization settings with context-dependent measures of quality" (p. s117). While IDR collaborations are quickly becoming the norm (Mansilla, 2006; Trochim et al., 2008), researchers and evaluators measuring research performance are struggling to develop valid approaches to quantify and examine the antecedents, processes, and outputs of interdisciplinary team science (Wagner et al., 2011). According to Klein (2008), evaluation of IDR remains one of the "least-understood aspects" of the phenomenon (p. S116).

Because there is no set standard, evaluation of IDR has been carried out in many forms. Researchers may choose to focus on the antecedents (inputs), processes, outputs, and/or outcomes associated with IDR (Stokols et al., 2003; Wagner et al., 2011). Antecedents include center bureaucratic and structural issues, the physical environment in which the research takes place, and the values and expectations of team members. Process evaluations include intra- and interpersonal communication, and examination of the activities that are done to carry out IDR (Stokols et al., 2003). Output evaluations focus on measuring the scientific products of IDR, as well as the way the scientific products have been shaped by the process of IDR. Outcome evaluations focus on the overall effectiveness and value of IDR (Wagner et al., 2011).

Process studies of IDR (Hall, Feng, Moser, Stokols, & Taylor, 2008; K.L. Hall et al., 2008; Klein, 2008; Mâsse et al., 2008; Nash, 2008; Stokols et al., 2003; Stokols et al., 2010; Stokols, Harvey, Gress, Fuqua, & Phillips, 2005; Trochim et al., 2008) and output studies of IDR (Leydesdorff & Rafols, 2011; Morillo, Bordons, & Gomez, 2001; Pei & Porter, 2011; Porter, Cohen, Roessner, & Perreault, 2007; Porter et al., 2008; Porter & Youtie, 2009; Rafols & Meyer, 2007, 2010; Rafols, Porter, & Leydesdorff, 2010; Rinia, van Leeuwen, & van Raan, 2002; Schummer, 2004; Tijssen & van Raan, 1994; van Raan, 1999; Zitt, 2005) are commonly found in the literature. Because the process of integrating research teams is more difficult to observe and measure, evaluation studies typically tend to focus more on the outputs of IDR, as they are more easily identified in published literature (Wagner et al., 2011). For these types of studies, bibliometrics are commonly used. Bibliometrics “involve the quantitative assessment of the occurrence of certain events in the scientific literature, as opposed to the analysis and interpretation of the literature's content" (Rosas, Kagan, Schouten, Slack, & Trochim, 2011, p. 1). Bibliometrics have been used as part of the larger evaluation process of several large publicly-funded research programs (Campbell et al., 2010; Hicks, 2004; Norman et al., 2011; Trochim et al., 2008).

One commonly used bibliometric analysis is co-authorship of scholarly publications (Porter et al., 2008). Some argue, however, that changes in numbers of co-authors could indicate a higher degree of IDR for study participants, but should not be taken as evidence alone as co-authorship does not necessarily mean the co-authors are from different discipline areas or fields of research (Porter et al., 2008). Another way to approach co-authorship analysis is to examine the disciplinary affiliations of co-authors (Qin, Lancaster, & Allen, 1997; Qiu, 1992). Other bibliometric approaches include the examination of citations in research articles to articles from other fields (Porter & Chubin, 1985; Tomov & Mutafov, 1996), citations to a specific set of articles (van Raan, 1999), and co-word analysis (Tijssen, 1992; Tijssen & van Raan, 1994). Some studies have also examined journal impact factors, journal and field performance indicators, or 5-year journal and field impact factors (Trochim et al., 2008). Finally, several studies have been published that attempt to understand the interdisciplinarity of a set of articles by categorizing them according to the subject categories of their journals according to the ISI Web of Science (WOS) subject categories (SC) (Glänzel, Schubert, Schoepflin, & Czerwon, 1999; Ponomariov & Boardman, 2010; Porter, Garner, & Crowl, 2012; Porter & Rafols, 2009; Porter et al., 2008; Porter & Youtie, 2009).

While many of the studies mentioned above have focused on the interdisciplinarity of fields of research, university departments, or specific grant activities, few studies have examined the effects of participation at an IDR center on the publication patterns of its participants (Ponomariov & Boardman, 2010; Porter et al., 2008). A need exists, therefore, for further study into the effects of participation in IDR center research teams on team members' publication and collaboration behaviors, as well as the factors that contribute to these effects.

Purposes of the Study

The purposes of this study were to (a) assess the early effects of affiliation with an interdisciplinary research center on participant publication and collaboration behaviors, and (b) determine what factors contributed to these effects for participants whose publication and collaboration behaviors were changed the most after affiliation. The study seeks to analyze the effect of a research center on the patterns and rates of publishing by university faculty using bibliometrics and interview data.

Importance of the Study

This study contributes to the research on evaluation of IDR centers, as relatively few studies have addressed the publication and collaboration behaviors of university faculty affiliated with IDR centers. In times of extreme budget deficits and spending cuts, it is important to demonstrate the effects federally-funded research centers have on the production of new knowledge. Thus, changes in publication outputs of scientists related to federal spending are of great interest to science policy makers. Additionally, as IDR centers are expected to foster collaborative networks that synergize across disciplines to further research and development, bibliometric studies showing co-authorship across institutional and disciplinary boundaries are also important (Klein, 2008; National Academy of Sciences, 2004; Stokols, Hall, Taylor, & Moser, 2008).

Context of the Study

NSF has recognized for a number of years that IDR is a means for accelerating scientific discovery, and the agency has provided support for this type of research through a variety of solicitations (National Science Foundation, 2010). One avenue through which NSF fosters IDR is through centers that are created to "exploit opportunities in science, engineering, and technology in which the complexity of the research problem or the resources needed to solve the problem require the advantages of scope, scale, duration, equipment, facilities, and students" (National Science Foundation, 2011a, para. 1). One group of such centers is the Centers for Analysis and Synthesis (CAS) under the Directorate for Biological Sciences. Initiated in 1995, the CAS group was created to help organize and synthesize biological knowledge that is potentially useful to many stakeholders, including policy makers, government agencies, researchers, and educators. As of January 2012, five CAS centers are currently funded: The National Center for Environmental Synthesis (NCEAS), The National Evolutionary Synthesis Center (NESCent), iPlant, The National Socio-Environmental Synthesis Center (SESYNC), and The National Institute for Mathematical and Biological Synthesis (NIMBioS).

This study draws upon research conducted by researchers participating in working groups at NIMBioS. NIMBioS is a science synthesis center whose mission is to cultivate cross-disciplinary approaches in mathematical and biological fields and to develop a cadre of researchers who address fundamental and applied biological problems in creative ways. The center arises from a collaboration between the NSF and the other agency sponsors, the U.S. Department of Homeland Security and the U.S. Department of Agriculture, with additional support from The University of Tennessee, Knoxville (cooperative Agreement EF-0832858 between the NSF and the University of Tennessee, Knoxville). The center brings together researchers from around the world to collaborate across disciplinary boundaries and take an integrative approach to address a vast array of challenging research questions in biology.

NIMBioS supports a range of scientific activities across the spectrum of synthetic research in mathematics and biology. The main types of research activities supported at the center are working groups, investigative workshops, post-doctoral fellows, sabbatical fellows, and short-term visitors. Working groups are chosen to focus on major well-defined scientific questions at the interface between biology and mathematics that require insights from diverse researchers. Investigative workshops focus on a broader topic or a set of related topics, summarizing/synthesizing the state of the art and identifying future directions. Post-doctoral fellows propose synthetic projects that require an amalgam of mathematical and biological approaches. Sabbatical fellows come to NIMBioS for a few months to a year and may include a mixture of NIMBioS activities as part of their in-residence experience. Short-term visitors are supported to work on-site at NIMBioS for periods of one week to one month to foster synthetic research at the interface between mathematics and biology.

The focus of the current study is a selection of participants from six working groups. Like all research activities at NIMBioS, working groups are selected through a peer-review process that examines the merit and fit of the request for support. Selection of working groups is based upon the potential scientific impact and inclusion of participants with a diversity of backgrounds and expertise that match the scientific needs of the effort. Organizers are responsible for identifying and confirming participants with demonstrated accomplishments and skills to contribute to the working group. Working groups typically involve 10-12 participants and meet 2-4 times over a two year period, with each meeting lasting 3-5 days; however the number of participants, number of meetings, and duration of each meeting is flexible, depending on the needs and goals of the group.

Research Questions

The mission of NIMBioS is to cultivate an interdisciplinary cadre of researchers who address fundamental and applied biological problems. As one measure of interdisciplinary scientific research is publication output, it is important to understand the impact of the center on interdisciplinary publication and collaboration activities of its participants. This study employed both quantitative and qualitative methods to explore the temporal evolution of participant publication and collaboration characteristics before and after association with NIMBioS. The research questions around which this study was designed were:

1. **To what extent does affiliation with NIMBioS working groups affect participant publication output?**
2. **To what extent does affiliation with NIMBioS working groups influence the collaboration behaviors of participants?**
3. **To what extent does affiliation with NIMBioS working groups affect the interdisciplinarity of participant research?**
4. **For participants who show the greatest impacts in publication and collaboration behaviors, what factors contribute to this impact?**

Assumptions

This study was conducted under the following assumptions:

1. The data used to examine participants' publication histories was a valid representation of his/her corpus of work.
2. Demographic information provided by participants was valid.
3. Co-authorship of a paper indicated that the participants collaborated academically on the research.
4. Participants openly and honestly responded to interview questions.
5. Interview responses were not biased by the interview protocol's formulation and contextualization of the topic.

Limitations

Internal Validity

The design of this study is a single group interrupted time-series quasi-experiment. This design controls for several threats to internal validity, including maturation, statistical regression, and testing due to multiple observations over time. For example, these threats usually do not provide a plausible explanation for a shift in variable measurement between time 1 and time 2 that may not have occurred in the previous time periods under observation (Campbell & Stanley, 1963). Further, the testing threat does not apply to studies using bibliometric analysis.

Typical threats to internal validity for this type of design are instrumentation, selection, and history (Shadish, Cook, & Campbell, 2002). Instrumentation, however, is not a problem in this study as the data were retrieved from WOS, which is a standardized publication database. Selection is also not an issue as the study only includes faculty who were affiliated with NIMBioS working groups beginning in 2009, and continued with their respective working groups until they concluded. As the historical bibliometric data collected for participants only included those who met these criteria, no changes in publication and collaboration behaviors could be explained by attrition.

The threat of history, or the possibility that something other than affiliation with NIMBioS may have affected the changes in participants, is the biggest challenge to internal validity. Attributing the impact of research policies, such as those of an IDR center like NIMBioS, to specific research outcomes is a known challenge in research evaluation (Georghiou & Roessner, 2000). The history threat in the present study is overcome in a number of ways. First, the nature of the longitudinal study provides multiple observations of each faculty member before and after affiliation, improving the reliability of any evidence of changes in publication or collaboration behaviors after affiliation with the center. Second, the participants in the study come from a diverse array of disciplinary backgrounds, institutions, career, and educational paths. Errors in such a diverse group are likely to be uncorrelated rather than showing related trends due to sharing common characteristics beyond affiliation with the center. Third, the regression method used to analyze the bibliometric data allows for controlling for multiple factors that correlate with collaboration and publication activity, such as gender, academic rank, and whether or not someone is in a social science field. Fourth, NIMBioS affiliation is not a "one-shot treatment," but rather a continuous research experience that consists of two to four meetings over a two-year period. This continual exposure, as well as the focus during the two years on production of interdisciplinary publications, alleviates the history threat to some degree as participants are engaged in the research and publication process with their groups quite heavily during that time. Although this does not preclude participants in the study being involved in other endeavors that might impact their publication and collaboration behaviors, the amount of exposure does increase the plausibility that affiliation with the working group may contribute to any effects found. Finally, the use of interviews serves to elaborate on the history mechanism by collecting firsthand accounts from participants about their views of whether or not they felt like affiliation with NIMBioS had an impact on the changes seen in the bibliometric portion of the study.

External Validity

This is a bounded case study, representing one research center. As such, generalizability of results to other IDR centers is limited. While the results may not be widely generalizable, the methods used may be replicated for evaluation of other interdisciplinary collaboratories.

Other Validity Concerns

Another possible limitation was the use of a single database for searching publication histories of participants. Not all possible research outputs will appear in WOS; however, other peer-reviewed studies have used WOS to study various aspects of IDR with success (Glänzel & Schubert, 2005; Leydesdorff & Cozzens, 1993; Morillo, Bordons, & Gomez, 2003; Ponomariov & Boardman, 2010; Porter et al., 2007; Rafols & Meyer, 2007). While coverage is not complete in all areas of science, the National Science Board has stated that the journals indexed in ISI SCI and Social Science Citation Index (SSCI) "give reasonably good coverage of a core set of internationally recognized scientific journals, albeit with some English-language bias" (National Science Board, 2000). Despite the drawbacks of using the WOS SCs for citation analysis, it remains a commonly accepted, sound bibliometric practic for measuring IDR (Porter et al., 2008).

Finally, the researcher of this study was employed by NIMBioS as the internal evaluator. The researcher adheres to both the Guiding Principles for Evaluators (Shadish, Newman, Shcheirer, & Wye, 1995) and The Program Evaluation Standards (Yarbrough, Shulha, Hopson, & Caruthers, 2011), and took care to conduct the research with honesty, integrity, and objectivity.

Study Methodology

This study employed a mixed-method case study approach, using quantitative bibliometric data (Ponomariov & Boardman, 2010) along with qualitative data collected from interviews (Brinkerhoff, 2003). Qualitative demographic information was coded quantitatively for use in the study as well. The quantitative element of the study employed a single group interrupted time-series quasi-experimental design (Shadish et al., 2002). Publication history data for each participant in the study was collected and analyzed by year against several demographic control variables to understand what effect affiliation with NIMBioS had on publication behaviors of participants. The periodic measurements for each individual were analyzed using random-effects Poisson or negative binomial regressions using PASW Statistics for Windows, Release Version 19.0. Specifically, negative binomial regression was used when the data in a given model were overdispersed, and Poisson regression was used when overdispersion was not present (Long, 1997). These vigorous and flexible procedures have been used previously in peer-reviewed studies of longitudinal bibliometric data (Bornmann, Wallon, & Ledin, 2008; Breschi, Lissoni, & Montobbio, 2004; Ponomariov & Boardman, 2010; Zucker, Darby, Furner, Liu, & Ma, 2007).

In addition to regression analysis, Integration (I) and Specialization (S) scores were calculated for participants according to the method outlined by Porter et. al (2008). Both scores can be used as measures of the interdisciplinarity of given bodies of scholarly work (Garner, Porter, Newman, & Crowl, 2012; Porter et al., 2007; Porter et al., 2012; Porter & Rafols, 2009; Porter et al., 2008; Porter & Youtie, 2009). I is a measure of the spread of references of a given paper or body or research to measure the degree of integration across discipline areas as indicated by the span of WOS SCs cited. S scores also reflect disciplinary diversity. While I reflects the breadth of referencing by researchers, S reflects the breadth of SCs in which researchers publish (i.e. the journals in which the researchers' papers themselves are published). Both scores take into account not just how many different SCs are engaged, but how "distant" they are from each other based upon cross-citation patterns for all WOS journals in 2007 (See Chapter 3 for further detail). Both I and S scores were calculated only for participants who had published at least three articles in both the pre and post periods of the study (Porter et al., 2008).

The qualitative element of the study consisted of collection of interview data using the Success Case Method (SCM) (Brinkerhoff, 2003). Originally created to evaluate the effect of training on business goals, the SCM was designed to determine the factors that contribute to the most successful users of a new method, tool, or capability that was gained from a training intervention. The SCM is conducted in five steps: focusing and planning a success case study, creating an impact model that defines what success should look like, designing and implementing a data collection instrument to search for best (and sometimes worst) cases, interviewing and documenting success cases, and communicating findings, conclusions, and recommendations. For the current project, the SCM was used to interview a selection of study participants who demonstrated the most change in publication and collaboration behaviors since their affiliation with NIMBioS to determine (a) what benefits (if any) participants felt they achieved as a result of participating in their working group, and (b) what factors (if any) participants felt may have contributed to the impact of NIMBioS affiliation on their publication and collaboration behaviors (Brinkerhoff, 2003). Participant interviews were be transcribed and analyzed for themes using QDA miner software. Analysis of resulting themes was conducted to determine what factors may contribute to the change in publication behaviors (Coffey & Atkinson, 1996).

Definition of Terms

Web of science (WOS): WOS is an online database through which researchers can access bibliographic and citation information for journal content and conference proceedings. The WOS consists of three databases: the Science Citation Index Expanded, the Social Sciences Citation Index, and the Arts & Humanities Citation Index.

Subject category (SC): SCs in WOS are assigned at the journal level by the editors responsible for the various subject areas within the database. Every article within a given journal is tagged with the categories of its respective journal. At the time of writing, there are 250 SCs in the natural and physical sciences, social sciences, and arts & humanities. Subject categories are reviewed annually and changes or additions are made in accordance to evolving areas of research. Annual changes to SCs are retroactive through the entire WOS database (Joint Information Systems Committee, 2011).

Interdisciplinary research (IDR): Much debate exists in the literature as to what constitutes a “discipline,” as well as the definitions of interdisciplinary, multidisciplinary, and transdisciplinary research. For the purpose of the present research, the researcher uses the definition put forth by the National Academies, which states that “interdisciplinary research is a mode of research by teams or individuals that integrates information, data, techniques, tools, perspectives, concepts, and/or theories from two or more disciplines or bodies of specialized knowledge to advance fundamental understanding or to solve problems whose solutions are beyond the scope of a single discipline or area of research practice" (National Academy of Sciences, 2004, p.188).

Integration: A measure of the spread of references of a given paper or body of research as reflected by the span of SCs cited. Scoring ranges from 0-1, with scores closer to 1 indicating more integration (or greater interdisciplinarity). Used in research evaluation as one measure of interdisciplinarity.

Specialization: A measure of the breadth of WOS SCs in which a researcher or group of researchers publishes. Measured on a scale of 0-1, with scores closer to 1 representing more specialization (or less interdisciplinarity). Used in research evaluation as one measure of interdisciplinarity.

Success case method (SCM): The SCM is a process for evaluating the effect of an intervention on its participants through in-depth interviews with the most successful implementers of the intervention's intended results. The SCM is conducted in five steps: focusing and planning a success case study, creating an impact model that defines what success should look like, designing and implementing a data collection instrument to search for best (and sometimes worst) cases, interviewing and documenting success cases, and communicating findings, conclusions, and recommendations (Brinkerhoff, 2003).

Organization of the Study

Chapter one of this study introduced the problem statement and described the specific problem addressed in the study as well as study context and design components. This chapter also contains information about the research questions addressed, assumptions, limitations, and key definitions. Chapter two presents a review of literature and relevant research associated with evaluating IDR teams. Chapter three offers the methodology and procedures used for data collection and analysis, including a description of participants in the study. Chapter four contains an analysis of the data and presentation of the results. Chapter five offers a summary and discussion of the study's findings, implications for the practice of evaluating IDR teams, and recommendations for future research.

CHAPTER 2

LITERATURE REVIEW

This chapter reviews the relevant literature to this study, and supports the need for further study into changes in interdisciplinary publication and collaboration behaviors of researchers after their affiliation with an IDR center. The growing incidence of IDR is explored, as well as the need to evaluate how and why it occurs. Quantitative methods to evaluate IDR will be discussed, as well as pros and cons of current bibliometric methods used in evaluation, such as co-authorship studies, citation analysis, spatial analysis, and studies that make use of multiple bibliometric indicators of IDR.

Rise of Interdisciplinary Research

The modern notion of "discipline" came about during the nineteenth century as the U.S. university was shaped by industrial forces that demanded trained specialists in order to keep their competitive edge (Klein, 1990). As the German model of the research university began to take hold in the U.S., disciplines became further specialized and developed (Wagner et al., 2011). Although disciplines were being defined during the late nineteenth and early twentieth century, they existed as independent silos for much of that time. In 1956, Boulding noted "specialization has outrun trade, communication between the disciplines becomes increasingly difficult, and the republic of learning is breaking up into isolated subcultures with only tenuous lines of communication between them" (p. 198). Although the Manhattan Project was a famously interdisciplinary endeavor undertaken in the 1940's, it was not until the 1960's and 1970's that a visible interdisciplinary presence could be seen on university campuses (Klein, 1990). In 1971, President Nixon signed the National Cancer Act, which funded a large research effort among multiple disciplines, including biostatistics, genetics, cell biology, bioethics, and clinical care (National Academy of Sciences, 2004). A catalyst for the interdisciplinary movement, cancer research was, and remains a highly interdisciplinary field due to the multitude and complexity of diseases studied in the field. Like cancer research, other interdisciplinary endeavors arose during the twentieth century in response to societal needs, such as magnetic resonance imaging, laser eye surgery, radar, the discovery of the structure of DNA, human genome sequencing, and manned space flight (Arnold and Mabel Beckman Foundation, 2011).

During the late 1960s and early 1970s, major federally funded organizations such as the NSF, the NIH, the Carnegie Foundation, the National Endowment for the Humanities, and the Fund for the Improvement of Post-Secondary Education began to promote interdisciplinary activities (Klein, 1990). Since the 1970s, interdisciplinarity in the sciences has been gaining momentum. A study by Chubin, Rossini, and Porter (1986) found that the number of papers covered by the ISI SCI database with the term ‘interdisciplinary’ in the title doubled from 1969 to 1972, then grew by 120 percent from 1973 to 1977, and finally grew an additional 95 percent from 1978 to 1982. Based on methods used in the Chubin et al. study, Braun and Schubert (2003) showed that the prevalence of the terms ‘interdisciplinary’ and ‘multidisciplinary’ in titles of papers in the same index grew exponentially from 1980 to 1999, doubling in a span of seven years.

The early twenty-first century has continued to see huge growth in IDR. In 2001, NSF launched the Nanoscale Interdisciplinary Research Teams program, which seeks to foster IDR in nanoscale science and engineering, with a funding requirement that each project have at least three co-principal investigators (Porter et al., 2008). The 2002 U.S. NIH roadmap for Medical Research includes initiatives that clearly recognize the importance of IDR as a catalyst for scientific discovery (Zerhouni, 2003). Examples of NIH initiatives that emphasize IDR include the National Cancer Institute's Transdisciplinary Tobacco Use Research Centers, Transdisciplinary Research on Energetics, and the Centers for Population Health and Health Disparities (Borner et al., 2010). In 2003, the U.S. National Academy of Sciences, along with the National Academy of Engineering and the Institute of Medicine, launched the National Academies Keck Futures Initiative (NAFKI), a $40 million, 15-year program whose objectives include "enhancing the climate for conducting interdisciplinary research, and breaking down related institutional and systemic barriers" (National Academy of Sciences, 2011). With high interest and increasing amounts of funding for these types of endeavors, IDR has been lauded almost universally as the way of the future (Porter & Rafols, 2009).

Methods for Evaluating Interdisciplinary Research

Along with the ever increasing interest and investment in IDR comes an interest in evaluating when and to what extent it occurs. While IDR collaborations are quickly becoming the norm (Mansilla, 2006; Trochim et al., 2008), researchers and evaluators measuring research performance are struggling to develop valid approaches to quantify and examine the outputs of interdisciplinary team science (Wagner et al., 2011). Although the importance of IDR is widely accepted, appropriate indicators to measure it are not (Morillo et al., 2001). To create quantitative indicators that allow researchers to compare researcher output regarding interdisciplinarity, bibliometrics are often used (Morillo et al., 2001; Wagner et al., 2011; Zitt, 2005). Bibliometrics is defined as "quantitative analysis to measure patterns of scientific publication and citation, typically focusing on journal papers…that may be used to help assess the impact of research…" (Sharif, Edward, Sonja, & Jonathan, 2009). Among the most commonly used bibliometric measures used to evaluate IDR are co-authorship studies, citation analysis, spatial analysis, and studies that make use of multiple bibliometric indicators of IDR.

Co-authorship

Co-authorship studies are commonly used bibliometric analyses of scholarly publications (Bordons et al., 2004; Porter et al., 2008). This approach assumes that IDR is achieved if researchers choose to co-author with those from different backgrounds (e.g. fields, departments, institutions, and geographic locations). Studies range from simply counting numbers of papers with multiple authors from different departmental affiliations (Bordons, Zulueta, Romero, & Barrigon, 1999; Hinze, 1999; Qin et al., 1997; Qiu, 1992), to analyzing patterns of co-authorship using social network analysis (Bellanca, 2009).

Counting numbers of papers co-authored by those with different departmental affiliations has been a popular way to quantify IDR in the past. One co-authorship study involving counts of papers co-authored across departmental affiliations was in the area of autoimmune disease research (Hinze, 1999). In this study, researchers found that 43% to 66% of all publications in selected European countries were cross-disciplinary according to this criterion. A limitation to this study was that it did not distinguish between papers with co-authors from only two different disciplines, and those with co-authors from three, four, or even more different disciplines. Providing levels of co-authorship would have helped measure the scope of the interdisciplinarity taking place.

In another study that looked at co-authorship based on departmental affiliation, Schummer (2004) conducted an analysis of over 600 papers published in eight nanoscience and nanotechnology journals to determine the extent of the presence of interdisciplinarity and multidisciplinarity in the nanoscale field. In this research, interdisciplinarity is defined as the interaction among disciplines (i.e. co-authorship among those from different departments), while multidisciplinarity is the presence of multiple disciplines, but without interaction (i.e. authors from different departments in the same journal, but who are not co-authoring). He found that nanoscale research, as compared to a classical disciplinary journal, showed only an average degree of interdisciplinarity, but a high degree of multidisciplinarity. When the journals in the study were analyzed separately, he found that each journal was quite representative of its own sub-field (e.g. “nano-physics”, “nano-chemistry”, “nano-electrical engineering”, etc.), and concluded that nanoscale research was made up of many mono-disciplinary fields rather than one large interdisciplinary field (Schummer, 2004).

Going a step beyond simply looking at co-authorship across fields, Qin et al. (1997) looked at the ideas of collaboration and interdisciplinarity separately. While co-authorship was seen as a measure of collaboration, interdisciplinarity in this study was measured by the number of disciplines represented in the journals cited by the papers. The researchers used the journal subject categories of Ulrich’s International Periodicals Directory to categorize the journals by discipline. The study, which looked at 846 papers published in the ISI SCI in 1992, found that roughly half of the papers were co-authored by researchers in different departments. The researchers analyzed the relationship between collaboration and interdisciplinarity, and found that higher levels of collaboration contributed significantly to the degree of interdisciplinarity in some disciplines (e.g. agriculture), but not in others (e.g. mathematics) (Qin et al., 1997). Qin et al. provided a more complete picture than previous studies of co-authorship by looking not only at the incidence of co-authorship, but its occurrence in conjunction with cross-disciplinary publication practices represented through citation analyses of representative papers.

Network analysis has also been used to measure IDR using co-authorship as the ties between actors. Bellanca (2009) examined a network of 50 researchers from the Biology Department at the University of New York. Disciplinary boundaries in this study were defined within the department as research foci of individual researchers, and co-authorship patterns were mapped using network analysis software to visualize linkages among the foci. Bellanca found links across most research foci (e.g. bioinformatics and mathematics, biophysics and biochemistry), indicating a high level of interdisciplinarity within the department. One group, molecular and cellular medicine, was found to have no collaborative co-authors within the department. This points to a possible limitation of using network analysis in co-authorship studies, which is boundary specification. Authors who may have collaborated with those outside of the department, in this case, may appear as though they are not practicing interdisciplinarity, when they may in fact be doing so. If the boundary of the study were expanded to include all of the co-authors of all of the faculty members in the department—including those outside of the department—this might have revealed a higher degree of interdisciplinarity. Of course, in a network analysis study boundaries must be set at a point that is feasible to the study, and the researcher in this case was interested only in analyzing the faculty members within the department.

While co-authorship studies offer a window into the analysis of IDR, there are several limitations to their use. First, co-authorship studies can be quite labor intensive for the researcher, as background information (such as departmental affiliation, research field, etc.) of co-authors are not readily available and must be obtained by researchers from curriculum vitas, surveys, web searches, or other means. The use of departmental affiliation as the disciplinary indicator is also problematic. While one might assume that departmental affiliation of an author would match his or her research expertise, research has shown this is not always the case. A study by Rafols and Meyer (2007) found that researchers' departmental affiliations are often unrelated to their original disciplinary training. For instance, one of their research subjects began a career in a physics department, moved to a school of medicine, then to a metallurgy department, then to a bioengineering organization, all while maintaining a research agenda focused on molecular motors. It is also possible that researchers may hold degrees in multiple disciplines or be affiliated with multiple departments (Porter et al., 2007). Another limitation to this method is that one must determine in advance a classification scheme to use to categorize the co-authors' departments or discipline areas. A scheme with too many categories may overestimate interdisciplinary activity, while one with too few will underestimate it (Bordons et al., 2004). A final limitation to using co-authorship analyses alone to measure IDR is that not all collaborations result in publications, and conversely, not all jointly published papers mean that all authors contributed in a collaborative manner (J. S. Katz & Martin, 1997). While co-authorship across varying fields is a valuable indicator of IDR, it should not be taken as evidence alone.

Citation analysis

Citation analysis is a bibliometric method that uses reference citations from scientific publications as the primary analytic tool (Garfield, Malin, & Small, 1978). It has historically been one of the most commonly used methods for measuring interdisciplinarity (Porter et al., 2008; Sugimoto, 2011; Wagner et al., 2011). The citation environment of a specific entity (whether a paper, journal, or body of work) is all journals that cite or are cited by that entity above a given threshold. The basic method for citation analysis involves choosing a body of documents to analyze, obtaining citation data for the documents, and categorizing the documents and citations into distinct disciplinary areas (Sugimoto, 2011). Most published studies involving citation analysis of IDR rely on the WOS SCs (Porter, Roessner, Cohen, & Perreault, 2006). The WOS assigns journals to standard subject categories based on a combination of citation patterns and editorial judgment at ISI, and any given journal may have more than one SC assigned to it (Morillo et al., 2003).

A commonly used bibliometric indicator using the WOS SCs is citations outside category (COC). This indicator was first introduced by Porter and Chubin (1985) in their study of 383 articles taken from 19 journals in the research areas of demography, operations research/management science, and toxicology. Citations were deemed COC when the main SC of the cited journal was different than that of the citing journal. The study found that almost 70% of citations belonged to the same SC as the citing journal, although inter-discipline differences were found, especially in the area of toxicology. Porter and Chubin found COC to be a robust indicator of IDR within a category across journals and within journals over time (Porter & Chubin, 1985). Morrillo et al. (2001) also used Porter and Chubin's COC indicator in their study of interdisciplinarity in the chemistry subdisciplines of polymer science and applied chemistry. They found that applied chemistry was more interdisciplinary not only according to higher levels of COC (65% vs. 41%), but also according to a higher rate of multi-assignation to WOS SCs (65% to 41%), and a higher percentage of references to the work from outside categories (71% vs. 54%).   Tomov and Mutafov (1996) created an interdisciplinarity index for journals in the area of fertility research using COC and references outside category along with number of citing and cited journals. The authors noted, however, that scientists, journal editors, and research policy managers were usually more interested in identifying how fields were relegated to one another than in obtaining an index number.

On the macro level, a few studies have examined cross disciplinary citations as an indicator of IDR as well. In its 2000 Science and Engineering Indicators Report, the National Science Board (NSB) examined citations outside area (COA) across 11 broad disciplines areas for papers published in 1997, again using the WOS SCs as a guide. The study found that biology was the most interdisciplinary, with 38% of citations designated as COA. Physics and Earth & space sciences were the least interdisciplinary, with approximately 18% and 17% COA, respectively (National Science Board, 2000). Van Leeuwen and Tijssen (2000) conducted a similar macro level study in which they analyzed citations of a set of papers from 2,314 journals from 1985 to 1995. The journals covered disciplines from the entire range of sciences and social sciences, and were categorized into 119 disciplines according to the WOS SCs. On average, the citation data in the study showed an overall COC rate of 69%, which was much higher than the macro level study conducted by NSB. In both studies, however, the most interdisciplinary disciplines were in the biomedical sciences. The higher level of interdisciplinarity in the Van Leeuwen and Tijssen study could be explained by a finer-grained approach to defining disciplines. Citation links among close categories would have been counted as interdisciplinary linkages in their study, whereas they would not have been in the NSB study. This discrepancy brings to point a limitation when conducting a COC (or COA) analysis of IDR at any level, which is that researchers must choose carefully and fully disclose the level at which they are aggregating the taxonomy of disciplines in the study, as breaking disciplines into smaller categories will result in more "cross-disciplinary" linkages.

Whether called citations outside category, cross-field citations, or cross-disciplinary citations, examination of citation flows from a body of work using the WOS SCs has been an informative method for analyzing IDR. The methodology is not without its limitations, however. While the classification of journals into subject categories by ISI is a convenient taxonomy to use in the study of IDR, some researchers perceive their research domains differently than the bibliometric depictions offered by WOS.

Leydesdorff and Cozzens (1993) reported that, based on cross-citation patterns of journals in their own field of sciences studies, journal clustering based on the WOS SCs did not match their own perceptions of their field. Another study by Rafols and Meyer (2007) found that journal based classification does not capture the main contribution of some articles. Using citation analysis of articles, they found that journal-based classification underestimated the contribution of structural biology, overestimated the contribution of cell biology, and could not be used for 35% of the references published in multidisciplinary journals.

Another issue with classification of papers by their journal's WOS SCs is that some journals are classified by WOS as multidisciplinary, including the highly popular *Nature*, *Science*, and *Proceeding of the National Academy of Sciences* (*PNAS*). This poses a problem for bibliometric studies in which these types of journals are common. Glänzel et al. (1999) attempted to overcome this shortcoming by reclassifying papers in multidisciplinary journals based upon their cited references. They found around 95% of *PNAS* papers could be classified in the life sciences subject category based on cited references, whereas *Nature* and *Science* papers could be classified into many different categories (with the majority being life sciences and physics) (Glänzel & Schoepflin, 1999).

Level of aggregation at which one creates disciplinary categories can also affect the level of interdisciplinarity detected, as evidenced in the work of Van Leeuwen and Tijssen (2000) and the National Science Board (2000). The more fine-grained the categories are, the more likely it is that a researcher will find citations outside of the citing journal's category, and vice-versa. Researchers should note the level at which they are analyzing their disicplines and provide comparative studies for perspective.

Finally, the use of WOS SCs for the measurement of IDR is biased towards articles in journals indexed in ISI databases. One study found that in most natural and medical science fields, between 80% and 95% of journals in the field are covered in the index; in the social and behavioral sciences, this number is projected to be much lower (Visser, Rons, van der Wurff, Moed, & Nederhof, 2003). While the study found that coverage was not complete for all sciences, the National Science Board has stated that the journals indexed in ISI SCI and SSCI "give reasonably good coverage of a core set of internationally recognized scientific journals, albeit with some English-language bias" (National Science Board, 2000). Despite the drawbacks of using the WOS SCs for citation analysis, however, it remains a commonly accepted, sound bibliometric practice for measuring IDR (Porter et al., 2008).

Spatial analysis

A relatively recent approach to analyzing IDR is through various types of spatial analysis using bibliometric data. These types of analyses are often accompanied by advanced visualization techniques, and attempt to measure the similarities or differences among the citations of the set of research products being evaluated (Wagner et al., 2011). Network analysis has been used in several spatial studies of IDR, with betweeness centrality as the main indicator of interdisciplinarity. Leydesdorff (2007) suggested that betweeness centrality may be used to measure IDR at the journal level, as a journal that is more often "between" other journals from different WOS SCs could be viewed as more interdisciplinary. Schummer (2004) suggested using betweeness centrality at the author level as well.

Maps of science are another relatively recent approach to spatial analysis of IDR. Noyons (2001) describes science maps as a" two or three dimensional representation of a science field, a 'landscape of science', where the items in the map refer to themes and topics in the mapped field, like cities on a geographical map" (p. 81). Generally, maps of science are derived from bibliographic databases, such as WOS, Scopus, or PubMed, but they may also come from other data sources. Maps are designed around the idea of similarity measures computed from correlation functions among pieces of information from bibliometric data. Items (e.g. co-authors, scientific topics, publications) are positioned in relation to each other in such a way that those that are cognitively related are closer together, and vice versa (Noyons, 2001; Rafols et al., 2010).

A common approach to mapping as a complementary method for measuring interdisciplinarity is the science overlay map developed by Leydesdorff and Rafols (2009). With this method, a network "base map" was created based on a journal-to journal cross-citation matrix using WOS SC data from 2007. Factor analysis of these SC-by-SC cross-citations provided "macro-disciplines" with which the base map was labeled. Researchers may overlay SCs of articles of interest on this base map to determine where their articles of interest fall. Carley and Porter (2012) used science overlay maps to complement their analysis of publications citing benchmark sample articles from various SCs for their "Diffusion" score, a new metric they developed. The maps provided a visual representation of not only the level of diffusion within the SC, but also which SCs cited a given benchmark with the greatest intensity. Garner, Porter, Newman, and Crowl (2012) used science overlay maps to illustrate differences in publications patterns for a set of researchers before and after participating in an NSF Research Coordination Network (RCN) program. The map illustrated that after participation, participants published in SCs that were less related to those in which they had published before participation.

Other spatial analyses of IDR focus on measuring diversity and coherence among discipline or subject areas of a given body of research. One such measure of diversity proposed by Stirling (2007), is a 3-dimensional concept incorporating variety (e.g. the number of distinct subject categories cited by a body of work), balance (e.g. the evenness of distribution of subject categories cited by a body of work), and disparity (e.g. the degree of difference among the subject categories cited by a body of work). Stirling's heuristic can be formulated into a generalized diversity index using a mathematical computation that includes the above metrics. Rafols and Meyer (2010) developed disciplinary diversity indicators to describe the heterogeneity of a bibliometric set of papers in bionanoscience from a top-down approach, which located each of the papers in one category on a global map of science. In conjunction with this analysis, they also developed indicators of network coherence to measure the intensity of similarity relations within the set using a bottom-up approach (e.g. co-citation analysis). They suggested that a combination of these two approaches might be useful for comparing emerging scientific and technological fields where new and controversial categorizations are accompanied by equally contested claims of novelty and interdisciplinarity.

Porter et al. (2007) developed two metrics for measuring interdisciplinarity of published research. The Integration Score (I) focuses on intellectual integration as defined by the National Academies Committee on Facilitating Interdisciplinary Research (2005). I measures diversity as defined by Stirling (2007), which distinguishes variety, balance, and disparity. Using subject categories of cited journals, the researchers calculate disparity within an article or among a body of research using a formula based on a SC cosine similarity matrix derived from an analysis of all 2007 WOS journal cross-citations. Scores calculated from 0 (no integration) to 1 (highly integrated) can compare the degree to which an article, body of work, or individual researcher utilized diverse intellectual resources when conducting his or her research. The Specialization Score (S) is similar to I, however, instead of measuring citations within a body of research, S considers the spread of SCs in which a body of research (i.e. set of papers) itself is published (Porter et al., 2007). In their analysis of the NSF program on Human and Social Dynamics (HSD), Garner and Porter (2012) found that I and S scores indicated that HSD-derived publications were notably more interdisciplinary than those of comparison programs. In another study of researchers participating in an NSF RCN program, I and S scores were also used as one indicator of interdisciplinarity (Garner et al., 2012). Researchers in this study did not find a significant change in I or S at the project level pre- to post-participation, but did fine a modest, yet statistically significant change in I on a per paper level for project participants.

While studies utilizing spatial analyses to study IDR appear promising, their biggest limitation to date is that they have not been thoroughly tested for robustness and generalizability across projects. While pilot studies have shown what researchers deem high levels of interdisciplinarity among indicators, there exists a lack of benchmarks among various areas of science against which to gauge these numbers. Also, more studies need to be conducted that look at the sensitivity of the various indicators to diversity in disciplinary categorizations to see what effect fine vs. coarse-grained taxonomies might have on some calculated indicators (Rafols & Meyer, 2010).

Multi-dimensional analysis

While most studies of IDR focus on one method for measuring IDR (e.g. co-authorship across departments, citation analysis, or spatial indicators of diversity among cited discipline areas), a few have created a multidimensional analysis to examine the phenomenon. Van Raan (2000) suggested using a convergence of three bibliometric approaches for studying the phenomenon of IDR:

1. The construction of a *research activity profile*: a breakdown of the scientific work published by a research group/institute into sub-fields, on the basis of the field-specific characteristics of the institute's own publications;
2. the construction of a *research influence profile*: a breakdown of the scientific work citing the work of a research group/institute into sub-fields on the basis of the field-specific characteristics of the institute's citing publications; and
3. the construction of *bibliometrics maps* of scientific fields in order to identify as objectively as possible structural relations between various subfields, as well as the relations of the subfields with other disciplines outside the central map of the field (p. 69).

The first two elements proposed by van Raan focus on science output of research groups or institutes, while the third method addresses where these outputs lie in the grand scheme of scientific output. The approach also lends itself to analysis of change over time within a research group or institute.

Ponomariov and Boardman (2010) took a multidimensional approach to examining the effect of university research centers on productivity and collaboration patterns of faculty affiliated with the center using several bibliometric indicators combined with survey data. Using a single group interrupted time series quasi-experimental design, the researchers looked at longitudinal bibliometric data—incorporating the whole publication histories for each member of the study—to measure number of publications per year, number of co-authors per year, number of ISI SCs per year, and number of collaborating institutions per year per author both before and after affiliation with the research center. The researchers controlled for several variables that might influence their measures of IDR, such as gender, year of doctorate degree, and whether or not a person was a social scientist. Using regression analysis, the researchers found that during the years in which faculty were affiliated with the research center, they were more likely to be productive, to produce more papers with industrial collaborators, to collaborate with colleagues and with other institutions, and to produce more interdisciplinary research. Further, they noted that junior faculty experienced greater gains than senior faculty in terms of publication productivity and collaborations. This multidimensional analysis was among the first to attribute these IDR outcomes to affiliation with a university research center.

Similar in some ways to the Ponomariov and Boardman study, Garner et al. (2012) conducted a multidimensional analysis of an NSF RCN program using a set of bibliometric measures and spatial analyses to determine how the program effected IDR. The study examined the publication patterns of a set of researchers three years before and three years after receiving RCN awards looking for increases in collaboration measures (numbers of authors per paper and number of institutions per paper), the extent of co-authorship and co-citation among award recipients, as well as I and S scores. In addition to these measures, the researchers calculated a diffusion score to examine the diversity of articles citing RCN articles using the ISI SCs, and also looked at article citations and journal impact factors. This study was unique in that is also utilized a comparison group of researchers who had applied for an RCN grant and been rejected. The study found evidence of a significant increase in collaboration (number of authors per paper and number of institutions per paper) for RCN groups, but not for comparison groups, and that there was also an increase in cross-citing of each other's work. The study also found that the articles generated by RCN project activities were more highly cited than those of the control group, appeared in higher impact journals, and were slightly more interdisciplinary. Taken together, these multiple measures provide a clearer picture of the IDR that resulted from the RCN support than would a single indicator.

Few studies have looked at integrating bibliometric indicators of IDR with information from interviews or surveys of researchers whose work is being examined in the study. The multidimensional approach of Sanz-Menendez et al. (2001) used data collected via survey from 671 Spanish scientists working in research teams in the areas of pharmacology and pharmacy, cardiovascular systems, and materials science to examine three dimensions of IDR: diversity in educational training and research specialization, cross-disciplinary research practices and behaviors, and diversity of ISI SCs of journals used in publications and citations of researchers in the study. This study found that interdisciplinarity is not acquired through academic courses (educational training), but through work experience of collaborating with other researchers. The study also found that collaboration by itself was not considered as reinforcing interdisciplinarity, although interdisciplinarity was indicated to some extent by 70% to 80% of the teams who indicated collaborating with external researchers. Finally, the study found that an average of two-thirds of the journal titles cited by researchers as publication or reference journals did not belong to the same ISI SCs as their own self-identified research background. The researchers found the three measures of IDR to be complementary in this study.

Rafols and Myer (2007) also relied on multidimensional analysis of IDR using data from both bibliometric indicators and interviews from researchers. Through five case studies of research teams in bionanotechnology, they examined five dimensions of IDR: affiliation, researchers' background, referencing practice, instrumentalities, and citations. They found a consistent high degree of cross-disciplinarily in what they deemed the cognitive practices of research (e.g., use of references and instrumentalities), but a narrower degree of cross-disciplinarily in the social dimensions (e.g., affiliations and researchers' backgrounds), and concluded that bibliometric indicators based on citations and references more accurately reflect the generation of IDR than do co-authors' disciplinary affiliations.

Multidimensional approaches to understanding IDR can be very useful as some argue that IDR is intrinsically a multidimensional concept that cannot be represented by one single indicator (Rafols & Meyer, 2007). A multidimensional approach appears particularly useful when the unit of analysis is a research team, center, or program. Garner et al. (2012) analyzed basic collaboration measures of authors per paper and institutions per paper in conjunction with citation and spatial analysis to provide a rich picture of an NSF RCN program's effectiveness at enhancing IDR among its participants. Ponomariov and Boardman (2010) analyzed the effect of university research centers on the productivity and collaboration patterns of university faculty using a longitudinal approach that measured number of publications per year, number of co-authors per year, number of WOS SCs per year, and number of collaborating institutions per year per author, both before and after affiliation with the research center. Coupling bibliometrics with interviews (Rafols & Meyer, 2007) and survey data (Sanz-Menendez et al., 2001) also provides a richer look at the incidence of IDR in research teams.

While multidimensional analyses may provide a clearer picture of IDR, especially among research groups and IDR centers, there are some limitations to this approach. One limitation to using multidimensional approaches that incorporate citation analyses is that citations to articles published in a given year rise quickly to a peak between two and six years depending on a number of factors, including disciplinary field in which the article was published (Amin & Mabe, 2000). This means that any study of the IDR outputs of a research group or institute that incorporates citation analysis would need to wait until at least six years after the first round of publications from the group were made public (although in the case of the natural and life sciences, the average peak in the number of citations has been shown to be in the third or fourth year after publication, and a 5-year period has been deemed appropriate for citation studies in these areas) (van Raan, 2005).

Another possible limitation to using a multidimensional approach is that it may be quite time consuming. Bibliometric analyses that incorporate only one indicator can take massive amounts of time to search, clean, and analyze the necessary data needed. Add to this additional bibliometric analyses or the possibility of interview scheduling, transcription, and analysis, and one project may take a considerable amount of time. Thus, it is important in the planning of any multidimensional analysis of IDR that the researcher keeps scale in mind. The rich information that may be gleaned from a multidimensional analysis may be well worth the effort of a well-planned project, however.

Conclusions and Summary

The rise in the incidence of IDR in recent years has seen a simultaneous increase in the number of studies attempting to measure when and to what extent it occurs. Although researchers are still working towards the best methods to evaluate IDR, bibliometric studies remain at the forefront of quantitative analysis in this field (Morillo et al., 2001; Wagner et al., 2011; Zitt, 2005). Most studies of IDR take a one-dimensional approach, using either one indicator of co-authorship, citation analysis, or spatial analysis as the main indicator of IDR. Studies taking these approaches tend to focus on IDR at the level of specific research areas or disciplines (Hinze, 1999; Porter & Chubin, 1985; Qin et al., 1997; Rafols & Meyer, 2010; Schummer, 2004). While these approaches are useful for providing broad overviews of IDR across large areas of information such as entire disciplines, they do not provide very detailed information at the level of the individual researcher who is at the heart of the IDR taking place. In addition, each method has its own limitations as well. Studies focusing on co-authorship analysis tend to define discipline area by departmental affiliation. This, however, can be a problematic definition as research has shown that researchers' departmental affiliations are often unrelated to their original disciplinary training (Rafols & Meyer, 2007). Citation analysis, while providing a rich level of information about the fields of study represented by the body of research being studied, is hampered by subjective issues of defining how many, and at what level the subject categories will be used to classify journals. Spatial analyses can be useful for providing indicators of IDR, but the methods still need to be tested for robustness and generalizability across projects. Given the limitations of one-dimensional approaches to measuring IDR, a multi-dimensional approach appears to be a more valid approach.

Multi-dimensional analyses of IDR take into account that IDR is a multi-faceted concept that cannot be represented by a single indicator (Rafols & Meyer, 2007). This approach has been used to examine the incidence of IDR in research teams (Rafols & Meyer, 2007; Sanz-Menendez et al., 2001), grant programs (Garner et al., 2012), and university-based research centers (Ponomariov & Boardman, 2010). Multi-dimensional analyses provide triangulation of data, so that one indicator alone is not used to determine the extent of IDR that has occurred in the body of work being investigated. While this triangulation can provide a richer view of IDR, it can be quite time consuming, so it is important to choose one's data sources and indicators carefully in this type of analysis to create a project that will provide the relevant information while remaining feasible to undertake.

While many of the studies mentioned above have focused on the interdisciplinarity of entire fields of research, few studies have examined the effects of participation at an IDR center on the publication behaviors of its participants (Ponomariov & Boardman, 2010; Porter et al., 2008). Although some multi-dimensional studies do incorporate survey or interview data from the researchers whose work is being examined, none have tried to determine what factors may have contributed to higher levels of interdisciplinarity in some researchers over others. A need exists, therefore, for further study into the effects of participation in IDR center research teams on team members' publication patterns and rates, as well as the factors that contribute to these changes.

CHAPTER 3

METHODOLOGY

This study employed a mixed-methods case study approach, using quantitative bibliometric data along with qualitative data collected from interviews. Qualitative demographic information was coded quantitatively for use in the study as well. The quantitative element of the study employed a single group interrupted time-series quasi-experimental design (Shadish et al., 2002). The qualitative element of the study consisted of collection and analysis of interview data using the SCM (Brinkerhoff, 2003).

According to an NSF funded national study of 300 research centers, case studies that include both quantitative and associated qualitative data may be the best method for describing and explaining how research center activities contribute to participant outcomes (Tash, 2006). The purposes of this study were to (a) assess the early effects of affiliation with an interdisciplinary research center on participant publication and collaboration behaviors, and (b) determine what factors contributed to these effects for participants whose publication and collaboration behaviors were changed the most after affiliation. Four research questions guided this study, as follows:

1. To what extent does affiliation with NIMBioS working groups affect publication output?
2. To what extent does affiliation with NIMBioS working groups influence the collaboration behaviors of participants?
3. To what extent does affiliation with NIMBioS working groups affect the interdisciplinarity of participant research?

4. For participants who show the greatest impacts in publication and collaboration, what factors contribute to this impact?

Study Design

The design of this research project replicated and expanded upon previous research (Ponomariov & Boardman, 2010) that examined the effect of a university research center on behaviors of affiliated researchers. Ponomariov and Boardman looked at the effects of affiliation with a university research center on the productivity and collaboration patterns of participating university faculty while controlling for several variables. The current study differs from the previous study, however, in three key respects:

1. While the previous study examined outputs of participants of a center that had reached the conclusion of its funding cycle (10 years), the present study seeks to know what (if any) early effects on participant collaboration and publication behaviors can be discerned.
2. The present study contains a qualitative element to attempt to understand the contextual influences of the group on changes in interdisciplinary collaboration and publication behaviors of participants.
3. The present study incorporates additional measures of interdisciplinarity, such as Integration and Specialization scores, and science overlay mapping.

Each participant in the study belonged to one of six working groups at NIMBioS, and met one to four times with their respective groups during the period of between April

2009 and August 2011 to address a research problem from an interdisciplinary standpoint. The most commonly reported outputs for these working groups were scholarly journal articles. To determine the effect of center affiliation on participant publication and collaboration behaviors, this mixed methods case study was conducted in two parts: a quantitative bibliometric study of peer-reviewed research articles of participants and a supporting qualitative study consisting of interview data collected from a purposive sample of participants.

Variables in regression models

The main independent variable of interest in the study was "NIMBioS affiliation," which was a dummy variable coded "1" for years in which a participant was affiliated with the center and "0" for years in which he/she was not. In this study, collaboration is defined as co-authorship on scholarly publications. Collaboration in scientific research and co-authorship of scholarly output are generally considered directly related. Glanzel (2002) exemplifies this point stating, "Collaboration in research is reflected by the corresponding co-authorship of published results, and can thus be analyzed with the help of bibliometric methods" (p. 46). Dependent variables used in the study include:

- the number of publications per year,
- number of distinct co-authors per year,
- number of distinct institutions of co-authors per year,
- number of distinct countries of co-authors per year, and
- number of distinct subject categories per year per participant.

While the first four dependent variables are self-explanatory, the subject categories variable requires some explanation. No universally accepted system exists for operationally defining discipline areas (Huutoniemi et al., 2010; Morillo et al., 2001; Porter et al., 2008; Porter et al., 2006; Zitt, 2005). One study that employed a multi-dimensional approach to defining disciplines of researchers in specific research groups found that the researcher discipline areas were defined differently with respect to their departmental affiliations, background (i.e. what they felt they practiced), references in project publications, instrumentalities (i.e. to which discipline their research instruments belong), and citation patterns (i.e. who the audience is for their research) (Rafols & Meyer, 2007). Clearly, a systematic categorization of disciplines must be used in bibliometric research. The most widely utilized taxonomy of research fields in bibliometric research are the WOS SCs (Porter et al., 2008). These categories are not identical to “disciplines” in that they are more fine grained. SCs are assigned to journals based on a combination of citation patterns and editorial judgment at the ISI, and any given journal may have more than one SC assigned to it. The set of SCs in which a researcher publishes can be used as a representation for the diversity of research areas in which a scientists works (Ponomariov & Boardman, 2010) .

Several control variables were also included in the study, as described in Table 1.

Table 1.
Explanation of control variables

Control variable	Explanation
Social science	Research fields vary widely in terms of productivity, and collaboration (Durieux & Gevenois, 2010). Social scientists have been found to have fewer co-authors than those in other scientific fields (Moody, 2004; Ponomariov & Boardman, 2010). This variable is coded 1 if the researcher self-identified a social science field as his or her primary field of study, and 0 if he/she did not.
Gender	Including gender as a control variable is warranted as studies have shown that female scientific productivity lags behind males (Cole & Cole, 1973; Long, 1992). Another study found that males are more likely to produce interdisciplinary research (Ponomariov & Boardman, 2010). This variable is coded 1 for male and 0 for female.
Tenured	It is important to assess the impact of affiliation with NIMBioS on junior faculty, especially regarding productivity, which is a primary criterion for tenure. This variable is coded 1 for study members who held at least the rank of Associate Professor during the year he or she affiliated with the center and 0 for those who did not. All participants in the study held tenure-track positions.
Year of PhD Degree	Year of PhD is important to include as scientists who received their degrees more recently may be more apt to adopt patterns of interdisciplinary collaboration than scientists who received their degrees when the IDR was not the norm.
Lagged publication productivity (lagged one year)	Past publication productivity has been shown to impact number of subsequent publications per year, number of collaborators per year, level of interdisciplinary research published, and number in institutions collaborated with (e.g., more productive scientists are more likely to be capable of higher numbers of collaborations)(Ponomariov & Boardman, 2010).

For the interview portion of the project, the SCM will be used to interview the top six study participants who have shown the most change in publication behaviors since their affiliation with NIMBioS to determine (a) what benefits participants achieved as a result of participating in their working group, and (b) what factors contributed to the impact of NIMBioS affiliation on their publication and collaboration behaviors (Brinkerhoff, 2003). Further explanation of this portion of the project may be found in the Instruments and Data Collection section.

Study Context

This study was part of a larger evaluation project, and draws upon research conducted by scientists participating in working groups at NIMBioS, a science synthesis center whose mission is to cultivate cross-disciplinary approaches in mathematical and biological fields and to develop a cadre of researchers who address fundamental and applied biological problems in creative ways. Working groups typically involve 10-12 participants and meet 2-4 times over a two-year period, with each meeting lasting 3-5 days; however the number of participants, number of meetings, and duration of each meeting is flexible, depending on the needs and goals of the group. One of the key indicators of success for any given working group is the group's scholarly product output, which could include journal articles, book chapters, conference presentations, new research proposals, workshops, student educational products, or new software developed. This study focuses only on peer-reviewed journal articles, which is the most common and highly visible form of output from these groups.

Participants

Subjects of the study were selected from six working groups that had completed their meeting cycles. Although NIMBioS participants may be part of more than one working group, all participants selected for the study had participated in only one working group as of the end of 2011. Participants from the working groups were retrieved from the NIMBioS database, which holds information about all participants at the center (National Institute for Mathematical and Biological Synthesis, 2012). Each group began between April and July of 2009, and had conducted either three or four meetings by August 31, 2011. Groups had between 12 and 21 participants who attended at least one meeting, and comprised a total of 91 different participants. From this pool of 91 working group participants, 46 project participants were selected who met the following criteria:

1. Held a position of faculty researcher at a university: Postdoctoral researchers, university research staff, graduate students, government researchers, and those from private industry were not included in the study because their publication histories were not sufficient for analysis. (One postdoctoral participant who had been mislabeled in the NIMBioS database as an Assistant Professor was included in the study, however. This participant accepted a position as Assistant Professor during his time with the group, met all other criteria for inclusion, and had sufficient publication history for analysis.)

2. Physically attended at least one working group meeting: Although each working group considered met physically 3 to 4 times, all members were not physically present at every meeting. Because much of the collaborative research was carried out off-site, members who attended at least one physical meeting were still considered viable members of their group.
3. Were still members of the working group at its final meeting: Participants in working groups may be added or dropped during the cycle of the group. Some participants may have attended the first or second meeting, but then ceased communication with the group. An assumption is made here that all working group members who are considered active participants at the last meeting are actively involved in the collaborative research and synthesis projects of the group.
4. Were not on the members of NIMBioS leadership team: Several members of the NIMBioS leadership team who participated in the working groups were excluded from the study to prevent conflict of interest as the study is part of the evaluation of the research center they direct.

The composition of the resulting pool of eligible participants had 39 males and 7 females. Eight participants reported their primary field of research as being in the social sciences, and 32 participants were tenured before becoming affiliated with the institute (See Table 2, Table 3, and Figure 1 for details about study participants).

Table 2
Demographics of participants

Variable	Number of participants	Percent of participants
Male	39	85%
Social scientist	8	17%
Tenured before NIMBioS affiliation	32	70%
	Median	Range
Number of meetings attended	3	1-4
Year of PhD	1995	1962-2008

Table 3.
Working group information

Working Group	Total no. of participants[a]	Participants selected for study	No. of meetings	Date of first meeting	Date of last meeting
Group A	16	8	3	4/16/09	11/4/10
Group B	21	4	4	4/27/09	8/15/11
Group C	12	6	4	5/26/09	12/14/10
Group D	16	10	3	6/7/09	5/16/11
Group E	14	5	3	6/10/09	9/13/11
Group F	17	13	3	7/27/09	2/10/11

[a] *Total number of participants includes participants who dropped out of the group along the way.*

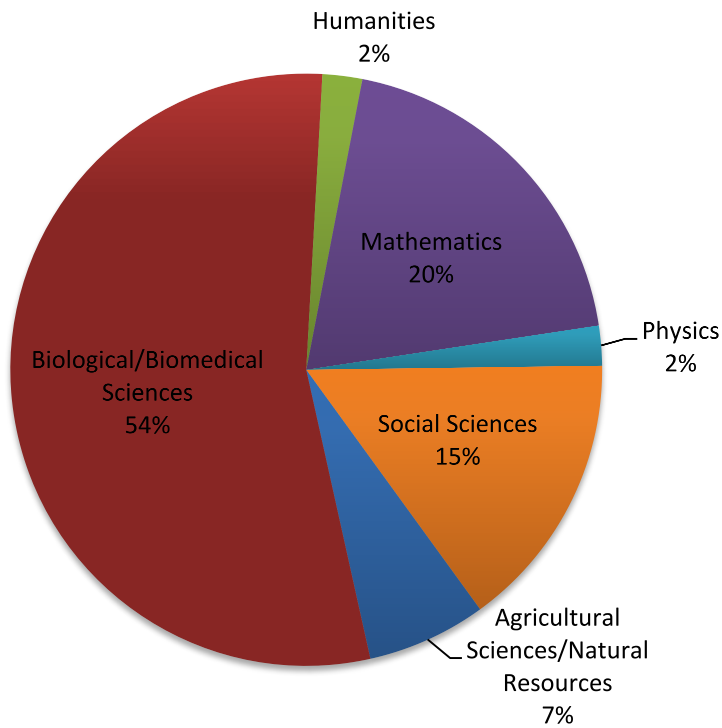

Figure 1. Primary fields of research self-identified by participants in the study

Instruments and Data Collection

For this project, three instruments were used to collect data: the WOS database, a participant demographic form, and a semi-structured interview (See Table 4). This section describes each of the instruments in detail.

Table 4.
Instruments used to collect data and dependent variables for each research question

Research Question	Dependent variables	Data Collection Instrument
Q1: To what extent does affiliation with NIMBioS working groups affect publication output?	Number of publications per year	Demographic survey WOS Database
Q2: To what extent does affiliation with NIMBioS working groups influence the extent to which researchers collaborate?	Number of co-authors, and institutions and countries of co-authors per year	Demographic survey WOS Database
Q3: To what extent does affiliation with NIMBioS working groups affect the interdisciplinarity of participant research?	Number of distinct subject categories per year, disciplinary participation, disciplinary frequency, Integration and Specialization scores	Demographic survey WOS Database
Q4: For participants who show the greatest impacts in publication and collaboration, what factors contribute to this impact?	Trends in impact factors	Semi-structured interview protocol

Participant demographic survey

All participants in NIMBioS activities were required to fill out a demographic survey online before their first visit to the center. The survey was aligned to the reporting requirements of the NSF and was designed by the researcher with input from the NIMBioS Director. The final instrument was hosted online via the University of Tennessee's online survey host mrInterview. Links to the survey were sent to the project participants three weeks before their arrival at NIMBioS. Reminder emails were sent to non-responding participants at seven and ten days past the initial contact. All participants filled out the survey for a response rate of 100%.

Web of Science

Changes in the publishing patterns of university faculty were examined using longitudinal data from before and after the faculty joined their respective working groups at NIMBioS. All publications for two-year "before" and "after" periods (2007-2008, and 2010-2011, respectively) for each participant in the study were downloaded from WOS. WOS is a multi-disciplinary bibliographic database available online that includes the Science Citations Index, Social Science Citation Index, and The Arts and Humanities Citation Index. As of April 1, 2011, these three indices covered over 49.4 million records in 12,032 high impact journals (Thomson Reuters, 2011). WOS SCs have been used in multiple interdisciplinary research evaluation studies (Glänzel & Schubert, 2005; Leydesdorff & Cozzens, 1993; Morillo et al., 2003; Ponomariov & Boardman, 2010; Porter et al., 2007; Porter et al., 2008; van Raan, 1999). WOS SCs are assigned to journals as a result of expert review of journal content and cited/citing patterns (Morillo et al., 2003).

Semi-structured interview

A semi-structured interview protocol based on the guidelines of the SCM was developed by the researcher for this study. The interview questions were guided by the research questions for the study. Each selected participant was interviewed using the same semi-structured protocol to determine (a) what benefits (if any) participants felt they achieved as a result of participating in their working group, and (b) what factors (if any) participants felt may have contributed to the impact of NIMBioS affiliation on their publication and collaboration activities (Brinkerhoff, 2003). Interview questions were as follows:

Lead in: From analysis of your publication and collaboration patterns before and after participating in the working group, it looks like you have shown a significant change in publication patterns. I just have a few questions to help us understand how your involvement with the group may have impacted these changes.

1. Why did you decide to become involved with the working group?
2. What do you feel was the most important benefit you got from participating in the working group?
3. As you think about your participation in the working group, what factors (if any) do you think influenced your collaboration activities the most?
4. As you think about your participation in the working group, what factors (if any) do you think influenced your publication activities the most?

5. What aspects (if any) of your group's leadership do you think contributed to the positive results you have experienced?
6. What aspects (if any) of the working group structure do you think contributed to the positive results you have experienced?
7. What (if anything) would you change if you participated in another NIMBioS working group that you feel would make the group more productive?
8. Do you have any further comments to add that we haven't discussed?

Analysis of Data

WOS Data

Following the method of Porter et al. (2012) publication records for each participant in the study were collected for two time periods: 2007-2008 as a "before" period and 2010-2011 as an "after" period. Publications from 2009 were excluded from the study as it would be difficult to ascertain which publications had been in process before affiliation with the center and which had not, as participants became affiliated with the center in early to mid-2009. As a number of publications arising from working group collaborations were reported as early as the end of 2009, beginning the "after" period at the beginning of 2010 appears to be an appropriate time frame (National Institute for Mathematical and Biological Synthesis, 2012).

Publication data were analyzed by year against several demographic control variables to understand what effect affiliation with NIMBioS may have had on publication and collaboration patterns of participants, following the method of

Ponomariov and Boardman (2010). The data were aggregated and analyzed at the level of individual participant by year using Vantage Point text mining software, which is used for analyzing filed tagged data such as WOS output files. After mining and aggregating relevant variables, the data were exported into a spreadsheet. The periodic measurements for each dependent variable were analyzed using random-effects Poisson or negative binomial regressions using PASW Statistics for Windows, Release Version 19.0. These analyses are well-suited to analyze this type of data as all dependent variables are count variables with positive integer values (Ott & Longnecker, 2010).

Regression Model Fit

Poisson or negative binomial regressions were used to analyze publication data for each participant. Specifically, Poisson regression was used when overdispersion was not present, and negative binomial regression was used when overdispersion was present (Long, 1997). Dispersion was analyzed by dividing the Pearson statistic by the degrees of freedom for that model. A dispersion parameter greater than 1.25 for models of this size indicated overdispersion, and the negative binomial model was considered (Hilbe, 2007).

In addition to the dispersion statistic, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) indicators of fit were also considered when selecting which model to use. The AIC and BIC "quantify the degree to which a given model represents an improvement over comparison models" (O'Connell & McCoach, 2008). When choosing between competing models, a smaller AIC and/or BIC value is considered a better indicator of fit for the data. For each regression model, a plot of the standardized deviance residuals versus the fitted values indicated no departure from the underlying statistical assumptions (See Appendix A). If the data are fit well, the residuals appear randomly scattered around the 0 on the Y-axis. When $n < 1000$, as in this study, standardized residuals greater than ±3.3 are considered outliers (Tabachnik & Fidell, 2007). One outlier was found with a standardized deviance residual value of 4.93 in the model for international co-authorship. Cook's distance (Cook's D) was calculated for this outlier to measure the influence of this particular case on the regression fit for the model. The rule of thumb is that an observation is influential if its Cook's D value is greater than 1.00 (Cook & Weisberg, 1982). The results indicated the outlier had a Cook's D value of 0.304, so no further action was taken to correct the data.

Data Integrity

After data collection was completed, data were examined for missing values and outliers using descriptive methods in SPSS. All data were found to be within their specified ranges.

As an additional check of data integrity, quantile-quantile (q-q) plots of the residuals for all regression models were reviewed to check for normality. The q-q plots revealed normal distributions, with few data points falling slightly above or below the normal line. Cook's distance (Cook's D) was calculated for each of these outliers to measure the influence of these particular cases on the regression fit. The results indicated that none of the outliers required further investigation (maximum Cook's D value for any outlier = 0.304).

Integration and Specialization Scores

Integration (I) and Specialization (S) scores were also calculated for participants according to the method outlined by Porter et. al (2008). Both scores can be used as measures of the interdisciplinarity of given bodies of work (Porter et al., 2007; Porter et al., 2012; Porter & Rafols, 2009; Porter et al., 2008; Porter & Youtie, 2009). I and S scores take into account not just how many different SCs are engaged, but how distant they are from each other.

I is a measure of the spread of references of a given paper or body or research to measure the degree of integration across discipline areas as indicated by the span of WOS SCs cited. The basic steps for calculating I for a body of research are:

1. Download the full record plus cited references for the papers of interest from WOS.
2. For each of the papers, and for each of the papers' references, identify the journals in which they appear.
3. Match each cited journal to its respective cited SC.
4. Create a matrix of cited SCs by cited SCs for the body of research.
5. Calculate I from this matrix using the following formula:

$$I = 1 - \sum_{i,j} p_i p_j s_{ij}$$

In this equation, p_i and p_j are the proportion of cited references corresponding to SC_i and SC_j in a given body of work. The summation is taken over all the cells of the body of work's cited SC x cited SC matrix. S_{ij} is the cosine measure of similarity between SCs i and j for cross–citation for a full year's worth of WOS articles in 2007

(Garner et al., 2012). The cosine values used in the calculation indicate relatedness of any two SCs. The values of S_{ij} are high (i.e. closer to one) when SCs $_i$ and $_j$ are co-cited by a high proportion of articles that cite one or the other. Conversely, the cosine value becomes closer to zero the less frequently two SCs are cited together (Porter & Rafols, 2009). The I score for a body of research increases as a paper cites more, relatively unrelated SCs.

S scores also reflect disciplinary diversity. S is based upon Leahey's definition of specialization as a researcher being "focused on one or a few sub-fields rather than spanning many" (2006). While I reflects the breadth of referencing by researchers, S reflects the breadth of SCs in which researchers publish. Porter et al. (2008) note that S and I are not in opposition to one another. For instance, one may integrate multiple discipline areas when writing to a relatively singular audience, or to a more diverse audience. On the other hand, one could pull mostly from knowledge sources in a single discipline area whether one is writing to a singular or more diverse audience. The basic steps for calculating S for a body of research are as follows:

1. Download the papers of interest from WOS, and count the number of publications in each subject category.
2. Create a matrix of publication SCs by publication SCs for the publications themselves.
3. Calculate S from this matrix using the following formula:

$$\boldsymbol{S} = \sum_{i,j} p_i p_j s_{ij}$$

Similar to I, in this equation, p_i and p_j are the proportion of publications themselves corresponding to SC_i and SC_j in a given body of work. The summation is taken over all the cells of the body of work's SC x SC matrix. S_{ij} is the cosine measure of similarity between SCs i and j for cross–citation for a full year's worth of WOS articles in 2007 (Garner et al., 2012). According to guidelines set forth by Porter et. al (2008), both I and S scores were calculated only for participants who had published at least three articles in both the pre and post periods of the study (N = 40).

Interview Data

The interview portion of the study follows the SCM, which is conducted in five steps: focusing and planning a success case study, creating an "impact model" that defines what success should look like, designing and implementing a data collection instrument to search for best (and sometimes worst) cases, interviewing and documenting success cases, and communicating findings, conclusions, and recommendations.

In the case of the current research, "success" is defined as the biggest change in publication and collaboration practices from before affiliation with the center to after affiliation. Instead of a survey, top cases were determined by calculating the Publication and Collaboration Index (PCI) change score described here. To determine which participants have shown the most change in publication behaviors, an analysis was performed on the change scores for average number of publications, collaborators, institutions, countries and number of subject categories per year from before and after participant affiliation with the center. Change scores in each of these categories were computed by subtracting the total number after affiliation from the total number before to create a composite score for each participant in each category. Difference scores were then summed to create a PCI score. PCI scores were ranked lowest to highest, and a gender-stratified sample of participants with the highest index scores (e.g. who showed the most change in publication and collaboration behaviors since their affiliation with NIMBioS) were invited for interviews. Gender stratification was used because (1) gender was shown to be a significant predictor of the dependent variables regarding publication and collaboration activities in all regression analyses conducted on bibliometric data in the study, and (2) no females were ranked in the top six regarding change in publication and collaboration behaviors. Email invitations were sent to the males with the top three PCI scores, as well as the four females in the study who exhibited positive PCI scores. After one week, emails were sent to the next three top males on the PCI scale until a total of three male interviews were scheduled. As only two of the four females agreed to interview, an additional male interview was conducted for a total of six interviews.

Participant interviews were transcribed and validated using the member check method (Glesne, 2006). Completed transcripts were shared with study participants, who were given the opportunity to provide feedback about whether or not they felt the transcripts represented their ideas accurately. Analysis of final transcribed interviews was conducted using QDA miner to determine what factors may have contributed to the change in publication and collaboration behaviors (Coffey & Atkinson, 1996).

CHAPTER 4

RESULTS

This chapter summarizes the descriptive, multivariate, and qualitative analyses in order to analyze the research questions and examine the impact of affiliation with NIMBioS on participant publication and collaboration activities. The number of observations (N) for the regression model for Research Question 1 (publication output) is 184, for all other regression models N =161. Dependent variables in each of the models are derived from publication data, and the variables are meaningful only if an individual has also published in a given year. For instance, while having zero publications in a given year is meaningful for analysis in Research Question 1, having zero collaborators in a year in which one has not published has no practical meaning (Ponomariov & Boardman, 2010). Results of the study are presented by research question.

Research Question 1

To what extent does affiliation with NIMBioS working groups affect participant publication output?

The dispersion parameter for the Poisson model was 1.28, indicating slight overdispersion. The dispersion parameter for the alternative negative binomial model was reduced to 0.98. AIC and BIC statistics were also lower for the negative binomial model, hence the data fit the negative binomial model better (O'Connell & McCoach, 2008).

The dependent variable was a count variable consisting of the number of journal articles a participant had published in the two years prior to affiliation with NIMBioS

(2007-2008) and also the two years after initial affiliation (2010-2011). The regression model did not find that affiliation with a NIMBioS working group was a significant predictor of publication output ($p = 0.963$).

The model estimated that past publication activity, however, was a significant predictor of publication output. For each paper published, the rate of publication in each subsequent year was estimated to increase by 15% ($p < 0.001$). Also, gender was shown to be a significant predictor of publication output. Males were estimated to publish 89% more publications than females ($p < 0.001$) (Table 5).

Table 5.
Variables affecting number of publications in year *i*

Parameter	IRR (95% CI)	Wald *z*	*p*
Affiliated with NIMBioS in year *i*	0.995 (0.985-1.005)	0.002	0.963
Number of publications in year *i-1*	**1.152 (1.120-1.184)**	**99.994**	**<0.001**
Year of PhD degree	1.024 (0.985-1.005)	1.024	0.312
Tenured before NIMBioS affiliation	0.973 (0.722-1.312)	0.031	0.859
Social science	0.802 (0.617-1.401)	2.75	0.097
Male	**1.886 (1.382-2.574)**	**15.992**	**<0.001**

For each unit increase in the explanatory variable, the number of publications changes by a factor given by the incidence rate ratio (IRR), shown here with a 95% CI. Significant effects (p < 0.05) based on the Wald z statistics are highlighted in bold.

Research Question 2

To what extent does affiliation with NIMBioS working groups influence the collaboration behaviors of participants?

Co-authorship

The dispersion parameter for the Poisson model was 6.16, indicating a high level of overdispersion. The dispersion parameter for the alternative negative binomial model was reduced to 1.21. AIC and BIC statistics were also lower for the negative binomial model, hence the data fit the negative binomial model better.

The dependent variable was a count variable consisting of the number of individual co-authors with whom a participant had published in the two years prior to affiliation with NIMBioS (2007-2008) and also the two years after initial affiliation (2010-2011). The regression model found that affiliation with a NIMBioS working group was a significant predictor of collaboration with co-authors. Affiliation with NIMBioS was estimated to increase number of co-authors by 40% (p = 0.006).

The model estimated that past publication activity was also a significant predictor of co-authorship. For each paper published in a previous year, the number of co-authors in each subsequent year was estimated to increase by 7% ($p < 0.001$). Also, gender was shown to be a significant predictor of co-authorship. Males were estimated to publish with 102% more co-authors than females (p = 0.002). Finally, social scientists were estimated by the model to have 45% fewer co-authors than non-social scientists ($p <$ 0.001) (Table 6).

Table 6.
Variables affecting number of co-authors in year *i*

Parameter	IRR (95% CI)	Wald *z*	*p*
Affiliated with NIMBioS in year *i*	**1.396 (1.100-1.770)**	**7.553**	**0.006**
Number of publications in year *i-1*	**1.067 (1.029-1.107)**	**12.287**	**<0.001**
Year of PhD degree	0.987 (0.873-1.002)	2.894	0.089
Tenured before NIMBioS affiliation	0.939 (0.629-1.376)	0.130	0.718
Social science	**0.559 (0.386-0.783)**	**10.956**	**<0.001**
Male	**2.022 (1.294-3.160)**	**9.558**	**0.002**

For each unit increase in the explanatory variable, the number of co-authors changes by a factor given by the IRR, shown here with a 95% CI. Significant effects ($p < 0.05$) based on the Wald z statistics are highlighted in bold.

Cross-institutional Co-authorship

The dispersion parameter for the Poisson model was 4.88, indicating a high level of overdispersion. The dispersion parameter for the alternative negative binomial model was reduced to 1.22. AIC and BIC statistics were also lower for the negative binomial model, hence the data fit the negative binomial model better.

The dependent variable was a count variable consisting of the number of distinct institutions of individual co-authors with whom a participant had published in the two years prior to affiliation with NIMBioS (2007-2008) and also the two years after initial affiliation (2010-2011). The regression model found that affiliation with a NIMBioS working group was a significant predictor of collaboration with co-authors from outside institutions. The model estimated that affiliation with NIMBioS increased cross-institutional co-authorship by 45% ($p = 0.002$).

The model estimated that past publication activity was also a significant predictor of cross-institutional co-authorship. For each paper published in a previous year, cross-institutional co-authorship was estimated to increase by 7% ($p < 0.001$). Also, gender was shown to be a significant predictor. Males were estimated to have 96% more cross-institutional collaborations than females ($p < 0.001$). Finally, social scientists were estimated by the model to have 38% fewer cross-institutional co-authors than non-social scientists ($p = 0.009$) (Table 7).

Table 7.
Variables affecting number of cross-institutional co-authors in year *i*

Parameter	IRR (95% CI)	Wald *z*	*p*
Affiliated with NIMBioS in year *i*	**1.453 (1.149-1.837)**	**9.757**	**0.002**
Number of publications in year *i-1*	**1.070 (1.029-1.112)**	**11.686**	**<0.001**
Year of PhD degree	0.986 (0.971-1.000)	3.666	0.056
Tenured before NIMBioS affiliation	0.819 (0.551-1.217)	0.976	0.323
Social science	**0.621 (0.434-0.888)**	**6.820**	**0.009**
Male	**1.963 (1.298-2.969)**	**10.217**	**<0.001**

For each unit increase in the explanatory variable, the number of cross-institutional co-authors changes by a factor given by the IRR, shown here with a 95% CI. Significant effects (p < 0.05) based on the Wald z statistics are highlighted in bold.

International Co-authorship

The dispersion parameter for the Poisson model was 1.22, indicating an acceptable level of dispersion. AIC and BIC indicators of fit also confirmed the Poisson model to be a better fit for this model than the negative binomial model. Thus, a Poisson regression was used for this analysis.

The dependent variable was a count variable consisting of the number of countries of individual co-authors with whom a participant had published in the two years prior to affiliation with NIMBioS (2007-2008) and also the two years after initial affiliation (2010-2011). The regression model found that affiliation with a NIMBioS working group was a significant predictor of international co-authorship, and estimated that affiliation with NIMBioS increased international co-authorship by 21% ($p = 0.042$).

The model estimated that past publication activity was also a significant predictor of international co-authorship. For each paper published in a previous year, the number of international co-authors in each subsequent year was estimated to increase by 6% ($p < 0.001$). Also, gender was shown to be a significant predictor. Males were estimated to have 43% more international co-authors than females ($p = 0.041$). The model also estimated that tenured professors collaborated with 31% fewer international co-authors than their non-tenured counterparts. Finally, year of PhD attainment was estimated by the model to be a significant predictor, although the effect was slight. For each year of increase in year of PhD attainment, participants had 0.01% fewer international co-authors ($p = 0.005$) (Table 8).

Table 8.
Variables affecting number of international co-authors in year *i*

Parameter	IRR (95% CI)	Wald *z*	*p*
Affiliated with NIMBioS in year *i*	**1.207 (1.007-1.446)**	**4.149**	**0.042**
Number of publications in year *i-1*	**1.059 (1.029-1.091)**	**15.087**	**<0.001**
Year of PhD degree	**0.985 (0.975-0.996)**	**7.843**	**0.005**
Tenured before NIMBioS affiliation	**0.692 (0.515-0.931)**	**5.926**	**0.015**
Social science	0.886 (0.665-1.179)	0.649	0.405
Male	**1.426 (1.015-2.002)**	**4.194**	**0.041**

For each unit increase in the explanatory variable, the number of international co-authors changes by a factor given by the IRR, shown here with a 95% CI. Significant effects (p < 0.05) based on the Wald z statistics are highlighted in bold.

Research Question 3

To what extent does affiliation with NIMBioS working groups affect the interdisciplinarity of participant research?

Disciplinary Participation

The leading subject categories in which participant research was published before and after affiliation with NIMBioS, ordered based on the frequency of "before" articles are listed in Table 9. In general, both the before and after groups cover similar broad areas of the biosciences and mathematics. The top SC in both cases is Ecology, followed by Evolutionary Biology and Zoology as either the second or third most prominent SC for each group. Although the distribution of articles in the top 20 SCs are similar before and after affiliation, the "after" group shows a slight decrease in the percentage of articles in Ecology, Evolutionary Biology, Zoology, and Genetics and Heredity. The "after" group also shows more concentration in general Biology, Applied Mathematics, Mathematical and Computational Biology, Economics, Environmental Studies, and Interdisciplinary Applications of Mathematics.

Table 9.
Distribution of publications among WOS SCs before and after affiliation

Subject Category	Rank Before	% of 276 articles	Rank After	% of 272 articles
Ecology	1	45%	1	39%
Evolutionary Biology	2	16%	3	10%
Biology	3	13%	2	18%
Zoology	4	8%	8	7%
Multidisciplinary Sciences	5	8%	5	8%
Genetics & Heredity	6	7%	20	2%
Mathematics, Applied	7	5%	6	7%
Environmental Sciences	8	5%	9	6%
Mathematical & Computational Biology	9	5%	4	9%
Biodiversity Conservation	10	5%	10	6%
Economics	11	5%	7	7%
Mathematics	12	4%	15	3%
Physics, Mathematical	13	4%	13	3%
Veterinary Sciences	14	4%	14	3%
Mathematics, Interdisciplinary Applications	15	4%	12	5%
Behavioral Sciences	16	3%	17	2%
Environmental Studies	17	3%	11	5%
Agricultural Economics & Policy	18	2%	23	1%
Cell Biology	19	2%	51	0%
Infectious Diseases	20	2%	16	2%

In Figure 2, the subject categories of the participants' articles indexed in WOS for two years prior to participation at NIMBioS and two years after initial participation on a network map of the WOS SCs are shown. The gray background intersections are the 224 WOS Subject Categories from the SCI and SSCI indices, located based on cross-citation relationships among all WOS journals in 2007 (from Rafols, Porter, and Leydesdorff, 2009). The 19 labeled "macro-disciplines" are based on factor analysis of that cross-citation matrix also. The gray lines linking the SCs are based on these overall WOS patterns, not the publications currently under study. Nearness on the map indicates a closer relationship among disciplines. Circular node sizes reflect the relative number of publications in the current study. SCs in which publications were more focused before, or in which there was no change in numbers of publications are lighter grey. SCs in which publications are more focused after affiliation appear as black nodes. SCs in which researchers published only after affiliation with the center are represented with white nodes.

A visual perspective of a shift in publication SCs toward mathematical fields, with more gray nodes in the Ecological, Biomedical, and Agricultural Science discipline areas, and more black and white nodes in the Mathematical Methods, Materials Science, Computer Science, and Economics, Politics & Geography discipline areas is given in Figure 2.

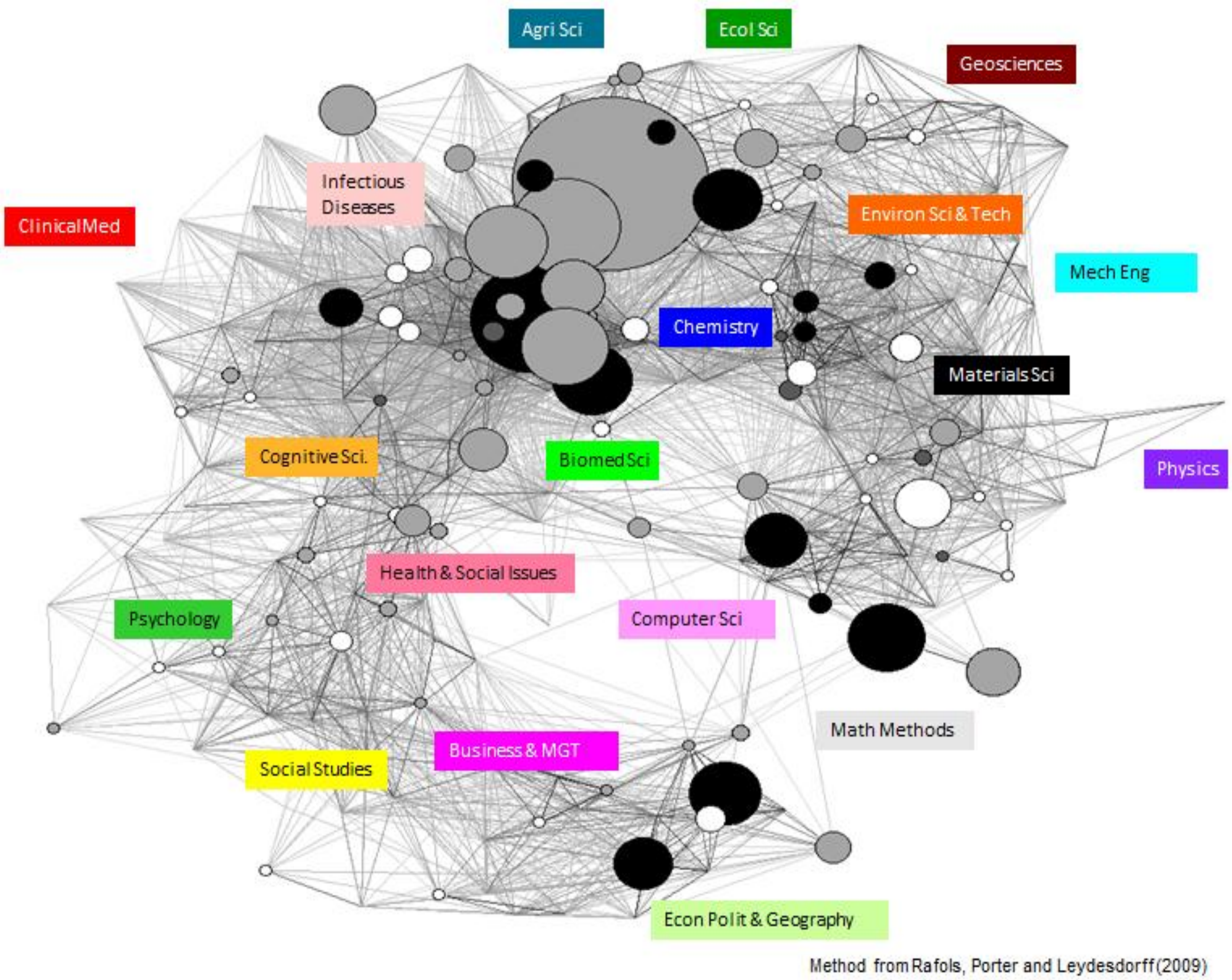

Figure 2. Working group participant publication "before" vs. "after" WOS SCs

Disciplinary Frequency

The dispersion parameter for the Poisson model was 1.17, indicating an acceptable level of dispersion. However, the dispersion parameter for the alternative negative binomial model was reduced to 1.02, however. Given that AIC and BIC statistics were equal for both models, the negative binomial model was chosen for this analysis as a dispersion parameter closer to one indicates a better fitting model (Hilbe, 2007).

The dependent variable was a count variable consisting of the number of WOS SCs in which participants had published journal articles in the two years prior to affiliation with NIMBioS (2007-2008) and also the two years after affiliation (2010-2011). According to the regression model, affiliation with a NIMBioS working group was not a significant predictor of number of WOS SCs in which a participant publishes ($p = 0.736$).

The model estimated that past publication activity, however, was a significant predictor of number of WOS SCs in which a participant publishes. For each paper published, the number of WOS SCs in which a participant published in each subsequent year was estimated to increase by 9% ($p < 0.001$). Also, gender was shown to be a significant predictor of WOS SCs in which a participant publishes. Males were estimated to publish in 50% more WOS SCs than females ($p = 0.010$) (Table 10).

Table 10.
Variables affecting number of WOS SCs in which participants publish

Parameter	IRR (95% CI)	Wald *z*	*p*
Affiliated with NIMBioS in year *i*	1.029 (0.873-1.212)	0.114	0.736
Number of publications in year *i-1*	**1.092 (1.070-1.117)**	**64.214**	**<0.001**
Year of PhD degree	1.002 (0.992-1.011)	0.131	0.474
Tenured before NIMBioS affiliation	1.102 (0.844-1.438)	0.512	0.718
Social science	0.907 (0.711-1.157)	0.618	0.432
Male	**1.501 (1.102-2.045)**	**6.640**	**0.010**

For each unit increase in the explanatory variable, the number of WOS SCs in which participant publish changes by a factor given by the IRR, shown here with a 95% CI. Significant effects ($p < 0.05$) based on the Wald z statistics are highlighted in bold.

Disciplinary Diversity

Integration

I is a measure of the spread of references of a given paper or body or research to measure the degree of integration across discipline areas as indicated by the span of WOS SCs cited. I is measured on a scale of 0-1, with scores closer to 1 meaning more integration of multiple disciplines in a body of research. I scores were calculated only for participants who had published at least three articles in both the pre and post periods of the study (N = 40). A Wilcoxon signed-rank test showed that affiliation with a NIMBioS Working Group did not elicit a statistically significant change in I scores in participants as a whole from the two years prior to affiliation to the two years post initial affiliation ($Z = -0.148$, $p = 0.882$). There was no change in mean I scores (0.55 pre and post).

Examination of individual changes in I scores showed that roughly half of those in the study increase their scores, while the other half decreased their scores. Changes in I scores from the pre to post period ranged from -0.62 to 0.41. No discernible patterns were found in the patterns of change in I scores, and no significant correlations were found associating changes in individual I scores with any of the independent variables in the study.

Specialization

S scores reflect the diversity of the SCs in which a body of research is published. S is also measured on a scale of 0-1; however, a higher S score indicates more specialized output (less disciplinary diversity). S scores were calculated only for participants who had published at least three articles in both the pre and post periods of the study (N = 40).

A Wilcoxon signed-rank test showed that affiliation with a NIMBioS Working Group did not elicit a statistically significant change in S scores in participants as a whole from the two years prior to affiliation to the two years post initial affiliation (Z = -0.542, p = 0.600). Mean S scores remained unchanged pre to post affiliation (0.56).

Examination of individual changes in S scores showed that roughly half of those in the study increase their scores, while the other half decreased their scores. Changes in S scores from the pre to post period ranged from -0.21 to 0.21. No discernible patterns were found in the patterns of change in S scores, and no significant correlations were found associating changes in individual S scores with any of the independent variables in the study.

Research Question 4

For participants who show the greatest impacts in publication and collaboration behaviors, what factors contribute to this impact?

The data for research question four results from six participant responses to semi-structured interviews (see Chapter 3 for methods). Participants involved in the interviews were told that they had been identified as showing a positive change in publication and/or collaboration behaviors after affiliation with NIMBioS, and that the purpose of the interview was to ascertain whether or not their affiliation with the center may have had any impact on these changes (See Appendix B for letter of invitation). Although both males and females were interviewed, no discernible differences between the working group experiences of the two genders were found during the interviews. All references to specific disicplines, research topics, institutions, etc., have been removed to protect the anonymity of the interviewees.

Five of the six participants indicated an overall positive experience with their working groups; however, one participant (Participant 1) reported an overall negative experience. Although the bibliometric portion of the study indicated that Participant 1 showed a positive change in collaboration behaviors after affiliation, this participant indicated the change was due to chance because none of the initial work that the group set out to do had been completed. Though the SCM approach does indicate the usefulness of interviewing "the most and the least successful participants," it was not the original intention of the present study (Brinkerhoff, 2003, p. 49). Therefore, although the initial purpose of the interviews was to document the most successful cases, Participant 1 will be treated as a "least successful" case and will be discussed separately from Participants 2-6.

Most Successful Cases

Reasons for involvement

Three of the five success case participants indicated getting involved with their respective working groups because the topic sounded interesting. One participant commented, "I thought he had a great idea and it sounded like a very good project. He showed me the list of people he wanted to invite and I suggested some people and I thought it would be a very interesting opportunity." Another simply stated, "The concept looked interesting so I thought it was worth a try." Another reason given by three of the participants was that they felt it was a good opportunity to work with other researchers.

“I was invited by the organizer of the working group, and I really was quite happy and felt quite honored to be invited to a NIMBioS meeting. I consider it a very important organization and it was a great opportunity for me to meet new people and to work together.” Another participant felt that the interdisciplinary composition of the group might help improve her research: “…as someone who does [Discipline A], for any opportunities to immerse myself in situations with more [Discipline B], I thought it would lead to better work in general.”

Most important benefit

Four of the five success case participants indicated that the most important benefit they got from participating in the working group was collaborating with researchers from other disciplinary fields with whom they had not previously worked. One participant’s comment:

> I think the greatest benefit was actually being able to work with really first class people. The whole working group, I felt were really top notch people, particularly people I didn't know before. I knew by name but not personally…I think that somebody really helped me produce something which I feel is useful.

Another participant said that the new collaborations have given him a fresh viewpoint on his already ongoing research:

> The greatest benefit was collaborating with people that I hadn't had the opportunity to work with before. The subject of the working group was along the lines of something I had been working on for some time, but I gained a different

> perspective from talking with people from other disciplines, particularly a [person who practices Discipline A].

Another participant indicated that the most important benefit she received was becoming aware of writing research in a language understood across disciplines:

> Always in the past I would write an introduction discussion that I wouldn't expect [Discipline Bs] would be able to read, so maybe I'll be a little bit more, I don't know if the word is 'careful.' I'm at least a little bit more aware that maybe there is a difference in the use of certain concepts… When I do write my papers now…I have to be a little bit more aware of knowing that [Discipline Bs] don't think of [Concept A] in the same context….There are serious [Discipline A] concepts, but they're not used the same way by [Discipline B] necessarily.

Effect on collaboration activities

In response to questions about how the working group affected their collaboration activities, all five success case participants indicated that affiliation with the working group lead them to collaborations with researchers from other disciplinary fields that would not have occurred had they not been a part of the group. One participant commented:

> I published with some people in the group that I had not published [with] before…I also published with people in other fields that I had not published in. I had not published with an [Discipline A] before the working group, so that was something new.

Another participant indicated that she developed a collaboration with a participant from another disciplinary field that was unexpected, as the topic of their project was not the original emphasis of the group:

> I was able to find overlap in something I was antecedently interested in thinking about-and it is very appropriate for a pure general [Discipline A] audience. This [person who practices Discipline B] and I were able to find that similar topics resonated with both [Discipline C] and science in general, and also the theoretical [Discipline B] audience. That was a surprise, and led to I think a really fruitful collaboration, a project that neither of us would have been able to do on our own.

Two participants indicated that affiliation with the working group lead to other types of collaborative activities as well. One participant's comments

> So subsequent to [the working group] I've been involved… in sessions at meetings, scientific meetings with at least one of the other participants, one of the collaborators on the paper, and I'm on a dissertation committee of one of the other co-authors.

Another participant indicated he became an advisor to a graduate student involved in his group: "…I became her PhD advisor, and she is finishing her PhD or defending her PhD around December, and she is essentially working on [Topic Removed] which I believe is quite a new application of existing methods." The same participant also indicated that he and other members of the working group obtained a major research grant together:

> … [Person B] who is my colleague, he's in [Discipline A] and I had never collaborated with him. Now he is the PI on this grant that was submitted, and I

> am co-PI. He persevered and involved some members of the working group, including [Person A] from [Institution A] and working group members from other universities. We got this major [funding agency removed] grant and [Person A] has been fundamental to do this, I think.

Other positive impacts of working group affiliation cited by two participants were not immediate results, but benefits regarding entering into collaborative research in the future. One participant's comments:

> Maybe it didn't make me more open to collaborations, but maybe it did give me skill in figuring out how to think about those collaborations, and when that was a viable option, right? Maybe more of a sense for when I could approach someone and suggest a collaborative project.

Another participant said:

> …I feel that I know these other folks now pretty well, the other collaborators on the paper; I really feel that it's given me a venue to talk with these folks again. If there are opportunities to follow-up on some of this work or other work it provides a sort of basis for doing that.

Effect on publication activities

Participants were asked how they felt affiliation with the working group may have affected their publication behaviors. In agreement with the bibliometric analysis, none of the five success cases felt that affiliation with their working groups caused an increase in their publication output (i.e. the number of papers they were publishing per year). Two of the participants, however, indicated that affiliation with the working group caused them to publish in journals in which they had not previously published. One participant commented:

> I was coauthor on one [paper] that we did publish, in [Journal A]. That is mainly for [Discipline As] and I haven't published there before...In the future I'm not sure if I will publish in [Discipline A] journals or continue to publish in [Discipline B] journals.

Another participant indicated that, although she did not publish in a journal that was new to her, she did gain confidence in her ability to publish in a high-impact journal in the future:

> …the journal [in which we published], [Journal A] is a high prestige journal. I guess it has given me some confidence that I would be able to publish in other journals of that type…it's always a big thing to get a paper in that. I think it's helped boost my feeling this would be a good journal to try again.

Group structure aspects

In response to questions about how the structure of the working group may have contributed to any positive results they experienced from the group, four of the five success case participants mentioned breaking into sub-groups as an asset, with one participant indicating the sub-group structure was one of his "most worthwhile exercises for collaboration on a paper." One participant's comments:

> …it took a little while, but fairly quickly we figured out that we were more effective, probably, when we spent more time divided into subgroups, then re-dividing and regrouping depending on the different projects and the different

> combinations of individuals involved than we were just as a group sitting on our own table talking about things serially. And so I found that part of the working group very useful… partly useful because it allowed the subgroup of people that did have a naturally associated interest, and those were easier groups for me to learn in. For instance, it wasn't as intimidating as ‘Hey wait, hold on. What are you talking about? That's the model you would use for this.’ The second reason I found this very useful is the very practical reason that we made a lot of progress in flushing out research plans, and even writing responsibilities, et cetera, in a way that I think really helped things along.

One participant detailed the process of generating sub-groups within his group:

> I remember at various points in our meetings, having the whiteboards filled with … sort of a grid of different projects. And then that involved the writing out of names of people potentially interested in those projects. I think that stage is where we got a lot of interesting groupings, and very inclusive groupings as well that cross cut a lot of people, so that maybe most of the people at the table had a sense of what the projects would look like. Then people were able to think ‘Oh, that's something I'm interested in. I don't know what I'd have to add, but the topic's interesting,’ and so the end result, maybe on average, each name was involved in maybe 50% of the projects or something like that. And so we had lots of overlapping smaller groups, which resulted in the scheduling difficulty of, ‘All right. Well, how do we have this group meet, and this group meet, when they are half overlapping individuals, and half not?’ But we worked through that so it

> more or less worked out. We had lots of different groups with shifting numbers of individuals in there. So even for the related project, you would have maybe six of us chatting about some project, and then four of us would go off to do other things, and then there would be the two remaining ones who had an associated idea, but they just wanted to hammer out the model for it and get it done. I think that was important.

Another aspect of group structure that was mentioned was an overall positive group atmosphere. Said one participant simply, "I felt from the beginning very welcomed," and another, "I just felt that I enjoyed it and I felt that everyone else seemed to be enjoying this very well." Included in this were having "good group dynamics" and the "right mix of people." One participant said the heterogeneous composition of her group contributed to the overall positive tone: "There was a mix of people from fairly old, established scientists down to graduate students and post-docs. That, I think, also contributed to a very, just whole positive atmosphere."

Leadership aspects

In response to questions about how the leadership of the group may have contributed to any positive results they may have experienced, all five participants mentioned the ability of their group leaders to keep the group organized. Said one participant, "I think probably our leader was very good and was very good at organizing things…We had an agenda." Another participant commented that his organizer established goals for the group, but allowed the group members latitude in how the goals would be reached:

> …I think he organized things very well. He laid out a very clear set of potential goals, and then the…we sort of, the working group divided into subgroups that pursued those goals. It was also a good mix of people. People from the more empirical side of this particular topic, and some very mathematical people. That combination worked very well. I think that just the way he organized things and let the groups sort of self-organize within the overall group into sub-groups and pursue these particular problems…I don't know, it just worked very well.

Another aspect of group leadership that was mentioned by three of the success case participants was the maintenance of a positive and welcoming atmosphere by their leaders. One participant's comments:

> The leadership impacted me greatly, because the leader of the group was extremely good. I'd say not just as a top scientist, but as someone who maintained a very positive atmosphere during the meetings at NIMBioS. I think that he was the right person to lead the group, and it just…I think it just worked out very well. I think that group, as a whole, was quite productive.

Another participant felt that the leadership's encouragement of younger scholars in the group added value to her experience:

> …I think that the leadership in the group was pretty attentive to those of us who are younger scholars, noting what we might be interested in, and encouraging our involvement so that we were more broadly involved than more senior researchers there….It felt very open and engaging in that way, which allowed me or

> encouraged me to think more creatively about what I actually could add to the process, and see places where my training could be relevant.

Finally, although all NIMBioS working groups have more than one organizer, four of the five participants indicated either explicitly or implicitly (e.g. referring to "he" rather than "they" in statements about leadership) that their group had one clear "leader." Said one participant, "There was mainly one leader. Even though there were several organizers it was mainly one leader who was involved." Another noted that it was apparent from the beginning of the group that one person would be in charge: "…there was one clear, clear leader…It was clear that that was going to be the case from the start, even among the organizers. It worked really well."

Suggestions for future working groups

In response to a question about what they would change if involved in future NIMBioS working groups, most participants could not think of any improvement. Two participants did mention that they would have liked to have been involved in more subgroups, but scheduling was difficult. One participant's comment:

> One thing I didn't like was there were a lot of parallel sessions at that point, which meant that it was hard to be involved in more than one thing. Some people managed to do it but it meant being in two places at once. That was a little hard.

One participant also indicated he would like to see the inclusion of graduate students (who are currently discouraged from participating in working groups in order to keep group sizes small, although at times are permitted to participate as observers). His comments:

> … I would allow the participation of a small number of graduate students that would make it…an even more energetic and stimulating working group. I think we had one graduate student…but I think incorporation of advanced graduate students, people that are dissertation stage, would be very useful… Because they have good ideas and they have a lot of energy. Even though a lot of the faculty were involved in the group and work extensively, we were also are tied in with a myriad of obligations…We had essentially one [graduate student] that participated, who was very effective, and the other participated from the outside– it would have been great had he been more involved. He was my PhD student– now a postdoctoral researcher–with the grant, at [Institutions A and B]. And that has been very good because he knew the material and now is working essentially with the [Discipline A] program, joining the grant that emerged from these efforts.

Least Successful Case

Reasons for involvement

Participant 1 reported becoming involved with his group initially because the topic and participants seemed a good fit for research he already had underway:

> This was a [Topic A] working group and I'm very involved in [Topic A] issues, and it seemed like a good opportunity to work with people from [Institution A] on some of these modeling efforts that we were trying to do. They seemed to have the people and the funds to do that part of the work.

Most important benefit

Participant 1 did not feel he got any benefit from participating in his working group. In fact, he felt that being in the group was a detriment to his research agenda. He commented, “I would say if anything [being in the working group] slowed work down that I had ongoing and accomplished absolutely nothing.”

Effect on collaboration activities

Although results from the bibliometric study indicated that Participant 1 showed an increase in collaborative activities after affiliation with his working group, he indicated that those activities were unrelated to the working group, and that most were from collaborations that were ongoing before the group started.

Effect on publication activities

Participant 1 also did not feel like affiliation with the working group had any impact on his publication activities. When asked about the changes seen in his publication behaviors from the bibliometric portion of the study, he had this response:

> Those were papers that were ongoing from before. My papers seem to come in clumps and none of that work was associated with [Topic A]. The only difference I guess were in some presentations, that I do every year and I've done every year, or every other year for 10 or more years, where I added some of the [Institution A] people on, being generous in that because I was going to talk about things that were from one slide, things that we were doing and hoping to do, to spur interest in this. I'm sorry I did that now.

Group structure aspects

When asked what aspects of group structure may have contributed to the negative results he experienced, Participant 1 pointed to lack of organization within the group, particularly among participants from one institution:

> The group that was working on this, myself and [Person A] from here at [Institution B], and also [Person B], [Person C] and [Person D] from [Institution A]. Basically each time we met we would get--from [Person B], [Person C] and [Person D]--after the initial report that they made of doing [Project A], which they finished over two years ago I think, we've just basically gotten these same identical reports for the last two years. With them saying that 'we want to do this' and 'we're going to go ahead and do this,' and then nothing happens. I don't know if they're too busy or if they're told 'that's number 20 on your list of priorities from this group and until you get the other 19 done you can't do that.' There was never a postdoc assigned to this to help with this work or anything. I don't know if it was an issue of priorities or what.

Coupled with the lack of organization, Participant 1 felt the wrong people were involved with the group. He felt that those involved were not in the group for the right reasons:

> If it was all people who actually had an interest in the topic, they would be more likely to do it. In this situation, the people there had no knowledge or interest in [Topic A]. They were just in the group for whatever reasons. Asking them to do work for something that they probably never would've done on their own, other than for whatever reason they were put in this group, may be a part of the issue.

Leadership aspects

Lack of communication and organization were cited as issues with leadership by Participant 1. A particular problem faced by this participant was that the organizers of the group were part of the institution that Participant 1 indicated was not completing the tasks they were assigned. His comments:

> Each time over the years that we met we discussed this and we wanted to continue with the process that we had started, but over time you start to get weary. I talked with [a group organizer] last spring about this and I think what precipitated then was two scheduled teleconferences. The first one, like I said before, they provided the same information they had provided a year and a half ago. The second one apparently they canceled but none of the rest of us knew they had canceled it. There were four of us e-mailing back and forth trying to find out what had happened, between here, someone else here in [State A], someone in [State B], and someone in [State C].

Suggestions for future working groups

Although Participant 1 had a negative experience with his working group, he indicated he would like to be part of another NIMBioS working group in the future, but would like to see others follow-through on their tasks:

> I actually would like to be involved in another [working group]…I think the idea and I think the way it's set up, at least from my perspective, is something that could be really productive. I guess what I would like to see changed is when

people say they're going to do something, they do it. That's not exactly a NIMBioS issue.

Summary of Results

The study found that affiliation with a NIMBioS working group has a significant positive effect on participant collaboration activities, and a moderate effect on publication activities, evidenced by participants publishing new SCs. Results from the regression analyses found that affiliation with NIMBioS working groups was a significant predictor for indicators of collaboration (i.e. number of co-authors, number of international co-authors, number of cross-institutional co-authors), but not for publication productivity (number of publications per year) or interdisciplinarity (number of WOS SCs per year). Qualitative analysis of interdisciplinarity showed a shift in publication SCs toward mathematical fields, with participants publishing less after affiliation in the Ecological, Biomedical, and Agricultural Science fields, and more after affiliation in the Mathematical Methods, Materials Science, Computer Science, and Economics, Politics & Geography discipline areas.

All five success case participants indicated that affiliation with the working group lead them to collaborations with researchers from other disciplinary fields that would not have occurred had they not been a part of the group. In agreement with the bibliometric analysis, none of the five success cases felt that affiliation with their working groups caused an increase in their publication output (i.e. the number of papers they were publishing per year). Two of the participants, however, indicated that affiliation with the working group caused them to publish in journals in which they had not previously published.

In response to questions about how the structure of the working group may have contributed to any positive results they experienced from the group, four of the five success case participants mentioned breaking into sub-groups as an asset. Another aspect of group structure that was mentioned was an overall positive group atmosphere. In response to questions about how the leadership of the group may have contributed to any positive results they may have experienced, all five participants mentioned the ability of their group leaders to keep the group organized. Another aspect of group leadership that was mentioned by three of the success case participants was the maintenance of a positive and welcoming atmosphere by their leaders. Also, four of the five participants indicated that, even though each group had multiple organizers, their groups had only one clear "leader."

The least successful case participant did not feel he got any benefit from participating in his working group. Although results from the bibliometric study indicated that Participant 1 showed an increase in collaborative activities after affiliation with his working group, he indicated that those activities were unrelated to the working group, and that most were from collaborations that were ongoing before the group started. When asked what aspects of group structure may have contributed to the negative results he experienced, Participant 1 pointed to lack of organization within the group, particularly among participants from one institution. Coupled with the lack of organization, Participant 1 felt the wrong people were involved with the group. He felt that those involved were not in the group for the right reasons. Lack of communication and organization were cited as issues with leadership by Participant 1. A particular problem faced by this participant was that the organizers of the group were part of the institution that Participant 1 indicated was not completing the tasks they were assigned. Although Participant 1 had a negative experience with his working group, he indicated he would like to be part of another NIMBioS working group in the future, but would like to see others follow-through on their tasks.

CHAPTER 5

CONCLUSIONS, DISCUSSION, AND RECOMMENDATIONS

Interdisciplinary research centers are typically presented as a means for exploiting opportunities in science where the complexity of the research problem calls for sustained interaction among multiple disciplines (National Research Council, 1987). According to Tash (2006), research centers are creating a new model for who performs science, as well as the impacts and purposes of the research. In FY 2011, NSF funded 107 research centers with a total of almost $300,000,000 (National Science Foundation, 2012). In FY 2012, NSF's Directorate for Biological Science estimated it invested close to $26,000,000 in its four Centers for Analysis & Synthesis alone, which includes the current research center under study (National Science Foundation, 2012). Because of the large amount of resources invested in IDR centers, a need exists to understand the impacts these centers have on the research behaviors of their participants, especially with regard to interdisciplinary publication and collaboration activities. There is also a need to determine what factors may contribute to the changes in their research behaviors (Tash, 2006).

The purposes of this study were to (a) assess the early effects of affiliation with an interdisciplinary research center on participant publication and collaboration behaviors, and (b) determine what factors contributed to these effects for participants whose publication and collaboration behaviors were changed the most after affiliation. The study sought to analyze the effects of a research center on the patterns and rates of publishing by university faculty using bibliometrics and interview data. This chapter summarizes the conclusions for each research question, provides discussion for these conclusions, and discusses implications for future research.

Conclusions

Research Question 1

To what extent does affiliation with NIMBioS working groups affect participant publication output?

Conclusion—Affiliation with a NIMBioS working group was not a significant predictor of publication output for participants in the study. Participant publication levels remained relatively stable overall from pre- to post-affiliation.

Research Question 2

To what extent does affiliation with NIMBioS working groups influence the collaboration behaviors of participants?

Conclusions—During years in which they are affiliated with NIMBioS, faculty are:

- more likely to collaborate with more co-authors;
- more likely to collaborate with more co-authors from institutions outside of their own; and
- more likely to collaborate with co-authors from other countries.

Research Question 3

To what extent does affiliation with NIMBioS working groups affect the interdisciplinarity of participant research?

Conclusion—Affiliation with NIMBioS does not lead faculty to publish in a larger number of WOS SCs than they did before affiliation.

Conclusion— After affiliation, participants showed a shift towards publishing in more mathematical fields, with participants publishing less after affiliation in the Ecological, Biomedical, and Agricultural Science fields, and more after affiliation in the Mathematical Methods, Materials Science, Computer Science, and Economics, Politics & Geography discipline areas.

Conclusion—Participants as a group did not cite more diverse references in their publications after affiliation than before according to the I measure of interdisciplinarity. On an individual level, roughly half of the participants showed an increase in interdisciplinarity, and half of the participants showed a decrease. No patterns in these changes could be detected.

Conclusion— Participants as a group did not show an expansion of their publication categories (i.e. WOS SCs in which they themselves are publishing) according to the S measure of interdisciplinarity. On an individual level, roughly half of the participants showed an increase in interdisciplinarity, and half of the participants showed a decrease. No patterns in these changes could be detected.

Research Question 4

For participants who show the greatest impacts in publication and collaboration behaviors, what factors contribute to this impact?

Most Successful Cases

Conclusion—Collaboration and publication factors noted by the most successful case participants that impacted their success included: 1) collaborations with researchers from other disciplinary fields that would not have occurred had they not been a part of the group; 2) publishing in journals in which they had not published before affiliation with the working group; and 3) connections made that will facilitate future interdisciplinary collaborations.

Conclusion— Group structure factors noted by the most successful case participants that impacted their success included: 1) breaking into sub-groups; and 2) an overall positive and welcoming group atmosphere.

Conclusion— Leadership factors noted by the most successful case participants that impacted their success included: 1) the ability of their group leaders to keep the group organized; 2) the maintenance of a positive and welcoming atmosphere by their leaders, and 3) emergence of one clear “leader” who took charge of the group’s daily routine.

Least Successful Case

Conclusion— Although results from the bibliometric study indicated that the least successful case participant showed an increase in collaborative activities after affiliation with his working group, he indicated that those activities were unrelated to the working group.

Conclusion— Group structure factors noted by the least successful case participant that impacted his lack of success included: 1) lack of organization within the group, particularly among participants from one institution; 2) the wrong people were involved with the group; and 3) lack of follow-through on tasks.

Conclusion— Leadership factors noted by the least successful case participant that impacted his lack of success included: 1) difficulty with communication and organization; and 2) lack of follow-through on tasks.

Discussion and Implications

The results of this study indicate that affiliation with a NIMBioS working group affects the collaboration, and to a lesser extent, publication behaviors of affiliated faculty in ways consistent with the mission of the center, which includes a goal to "address key biological questions by facilitating the assembly and productive collaboration of interdisciplinary teams"(National Institute for Mathematical and Biological Synthesis, 2007). Publication and collaboration behaviors can be seen as part of a researcher's scientific and human capital (S&T human capital). According to Bozeman, Dietz, and Gaughan (2001) S&T human capital can be defined as "the sum of an individual researcher's professional network ties, technical knowledge and skills, and resources broadly defined" (p.636). In other words, S&T human capital is the sum of an individual's capacity to carry out research. As such, positive shifts in collaboration and publication behaviors can be seen as increasing the S&T human capital of NIMBioS participants.

Collaboration Behaviors

Participants were shown to increase the number of collaborations through co-authorship on several indicators. Increased collaboration is seen as a benefit for a number of reasons. An often cited benefit is the synergistic effect of bringing together people with different skill sets, which increases the overall skill level of the entire team of collaborators (Franc, Luka, & Ferligoj, 2010; Sonnenwald, 2007). Co-authored publications are seen as well as having greater epistemic authority than single-authored papers, in that co-authorship confers the benefit of inter-subjective verifiability (Beaver, 2004; Wray, 2002). Collaborative research tends also to be more highly cited than other research (Haslam & Laham, 2009; Wray, 2002; Wuchty, Jones, & Uzzi, 2007). Citation counts of scientific articles have consistently been found to be correlated with research quality (Garfield et al., 1978; Lee, Schotland, Bacchetti, & Bero, 2002).

Participants in this study were found to increase not only their number of co-authors overall after affiliation with the center, but also their number of cross-institutional co-authors and also their international co-authors. This finding echoes that of other studies which found that affiliation with an IDR research group increased co-authorship (Garner et al., 2012; Ponomariov & Boardman, 2010). Several studies have shown that multiple institution papers are more highly cited than single institution papers, and that papers with foreign collaborators are more highly cited than domestic papers (Goldfinch, Dale, & DeRouen, 2003; Hoekman, Frenken, & Tijssen, 2010; Narin & Whitlow, 1990).

Katz & Hicks (1997) found that collaborating with a co-author from a domestic institution increases the average impact of a paper by 0.75 citations, while collaborating with a co-author from a foreign institution increases the impact by 1.6 citations. Increased citation counts not only increase the visibility of a researcher's work, but also the status of the researcher within his or her area of research, thus increasing his or her S&T human capital.

Publication Behaviors

The effect on publication behaviors of participants was less strongly represented, although still evident. Participants were not found to increase their publication output after affiliation with NIMBioS. This contradicts findings from other evaluation studies of IDR. Garner et. al (2012) found a significant increase in number of articles produced by participants in an NSF RCN program. Ponomariov & Boardman (2010) found that affiliation with an NSF Engineering Research Centers program increased the rate of publication incidence in participants by a rate of 1.5. Possible explanations for the difference in outcomes between the present study could be related to the time frame of the studies. The present study covered a total period of five years, while Garner's study covered nine years (1999-2001 as the "before" period and 2006-2008 as the "after" period). Ponomariov & Boardman's study covered the entire publication histories of participants, beginning in 1954, with participants being affiliated with the center between one and nine years. Thus, participants in both comparison studies were affiliated with their respective centers for longer time periods than participants in the present study, giving them more time to increase their S&T human capital in the context of the center, which may have affected their publication rates.

Gender

Gender was found to be a significant predictor for both publication productivity and collaboration. This is consistent with findings in the literature that indicate that women tend to have somewhat lower publication rates than men, and also tend to have fewer co-authors in general (Cole & Zuckerman, 1984; Long, 1992). Factors found to affect research productivity in women include marital status, career ambitions, age, parental status, amount of research time, degree of specialization, discipline, international work (collaboration and co-authorship), and academic rank (Allison & Long, 1990; Dundar & Lewis, 1998; Leahey, 2006; Prpic, 2002; Puuska, 2010). Interview data did not suggest that the experiences of females within the working group setting were markedly different from that of their male counterparts. One limitation to this conclusion, of course, is that only two females were interviewed. One female interviewed, however, indicated her 90-year-old ailing mother had come to live with her several years before she became affiliated with the working group, and that she felt this had negatively impacted her overall publication productivity during the last several years.

Interdisciplinarity

While no effect was found on publication rates of participants after affiliation, there was a slight trend toward publishing in more mathematical fields. Given that only 22% of participants self-identified as being in a primarily mathematical field, this can be taken as an indicator that affiliation may have caused participants from other fields to publish in more mathematical-oriented journals. Interview data support the conclusion that participants were publishing in journals outside of the ones in which they had published in the past, however, a participant-level analysis of self-identified field of study vs. publication SCs would need to be done before being able to say definitively if the shift toward publication in more mathematical fields was truly the result of participants publishing outside their fields, or was merely the result of the few mathematicians in the study publishing in mathematical journals in which they had not previously published.

One indicator of interdisciplinarity, I scores, did not change for participants. This echoes the findings of Garner et. al (2012), who found that I scores remained stable pre to post affiliation for researchers in an NSF RCN program at the same level as the present study (0.56). One explanation for this could be that part of the criteria for evaluation of NIMBioS working group applications is based on the breadth of geographic, institutional, disciplinary, and ethnic diversity. Because of this, these groups necessarily represent a broad swath of expertise coming into the group. Taken at the group level, the research knowledge resources, as reflected by their referencing patterns, did not change. This could be explained by the fact that referencing patterns are a reflection of collective resources and the group membership did not change from pre to post study. On an individual basis, however, there were fluctuations. Further research is needed to determine what factors may cause the I scores of some individual to increase, while others decrease after affiliation.

S scores, which reflect the diversity of SCs in with a body of research is published, also did not change pre to post affiliation. This also mirrors the findings of

Garner et. al. (2012), who found stable S scores of 0.49 to post affiliation for researchers in an NSF RCN program. Although this indicates that affiliation with NIMBioS did not lead researchers to expand their publication subject categories, it does not mean that researchers did not *change* the subject categories in which they were publishing. As an index, the S score looks at the similarity of SCs in which a person is publishing. So, if a researcher was publishing primarily in biology before affiliation, and publishing in biology and mathematics after affiliation, his S score would reflect that he was less specialized. However, if a participant was publishing primarily in biology before affiliation, and then switched to publishing primarily in mathematics after affiliation, the S score would likely remain unchanged. While this complete switch in publication practices would not be expected to be a long term event (e.g. a biologist would probably return to publishing in biology related journals) it is possible that the short-term effects of affiliation could cause participants to publish outside of their own fields, while neglecting to publish in fields in which they were previously publishing. This is especially plausible given that publication productivity was not found to increase in participants, but that participants were publishing with working group members from other research fields who may have influenced their journals of publication.

Contextual Influences

The experience of the success case participants can be associated with current research on contextual influences in interdisciplinary team science. Participants cited a positive, welcoming atmosphere as one of the contributing factors to their success in their groups. Greater social cohesiveness in a group has been shown to lead to increased productivity in several studies (Guzzo & Dickson, 1996; Kerr & Tindale, 2004). Another contextual factor related to group structure that was mentioned by several participants was breaking into subgroups to work on research problems. Research supports the claim of some participants that these smaller teams were more effective for coordination and decision making (Mullen, Symons, Hu, & Salas, 1989). An additional factor related to sub-grouping of individuals is the structural interdependence of member's tasks and rewards. One study of 150 teams of technicians in a corporation found that teams perform best when their tasks and outcomes are either solely group-oriented or solely individual-oriented (Wageman, 1995). Higher levels of task interdependence resulted in higher levels of cooperation and more positive interpersonal interactions among group members. As members of working groups broke into sub-groups, their tasks and related outcomes became oriented to small groups, which may have been an element in the positive outcomes associated with this factor.

Effective leadership was also cited as a contextual factor leading to participant success within the working groups. Several studies of IDR have suggested that group leaders strongly influence collaborative processes and outcomes (Morgan et al., 2003; Stokols, 2006). Participant cited characteristics of being able to organize the group, create a welcoming atmosphere, and encourage the participation of all participants are all described in research as characteristics of transformational leaders (Sivasubramaniam, Murry, Avolio, & Jung, 2002; Stewart, 2006). Teams who rated themselves higher on transformational leadership see themselves as more effective and achieve higher levels of performance (Sivasubramaniam et al., 2002).

The experiences of the least successful case participant (Participant 1) can be associated with current research on contextual influences in interdisciplinary team science as well. Participant 1's reasons for becoming involved with his working group to gain access to perceived expertise and funds to continue his ongoing research are in line with recent research in which 195 university professors were surveyed about the main benefits of collaboration. In response to an open-ended question about why they decided to join a collaborative project, the most common response (41%) was "co-author has special competence." Another common motive was "co-author has special data or equipment" (20%) (Melin, 2000). Although the reasons for joining the collaboration were positive, the experience with the group was not. While the negative experience of Participant 1 was unique among those interviewed, it is not unique to collaborative group research.

Participant 1 indicated that the trouble with the group was with a group of participants from the same institution who were not completing their tasks as assigned, and not communicating well with the rest of the group. This group was unique among NIMBioS working groups in having multiple participants from one institution, including two organizers from the same institution as several participants. Some studies have found that homogeneous research teams do not perform as well as heterogeneous teams on certain creative and intellectual tasks (Milliken & Martins, 1996; Wiersema & Bantel, 1992). Another study found that familiarity among team members can have a negative effect on team performance and communication over time, which supports Participant 1's claim that communication with the members from the singular institution worsened as the group continued (R. Katz, 1982). Participant 1's claim that airing his grievances with the organizers of the group did nothing to change the situation is also supported by research on team science that found that familiar teams exhibit less flexibility for change compared to teams of strangers (Okhuysen, 2001). Given that the organizers of the group were from the same institution as the members who were not completing their tasks as assigned, familiarity may have played a role in locking members into ineffective strategies over time because they were reluctant to modify pre-established roles and patterns of interactions.

Implications for Evaluation

IDR center evaluations are important for accountability, to improve center efficiency, and to assess outputs, outcomes, and impacts (Tash, 2006). Deciding who, what, and when to evaluate can be problematic, however, due to the complex nature of centers' research portfolios and missions and the multiple internal and external stakeholder groups that need to be addressed (Gray, 2008). Evaluators still know relatively little about how to evaluate the progress and effectiveness of large IDR centers (Trochim et al., 2008). Researchers and evaluators measuring research performance are struggling to develop valid approaches to quantify and examine the outputs of interdisciplinary team science (Wagner et al., 2011). Given the complex nature of evaluating IDR center impacts, the multi-dimensional approach taken in this study appears to be a valid and useful approach to evaluation of IDR center activities.

An important methodological aspect of the current study is the use of triangulation. Cohen and Manion (2003) define triangulation as an "attempt to map out, or explain more fully, the richness and complexity of human behavior by studying it from more than one standpoint and, in so doing, by making use of both quantitative and qualitative data" (p. 112). Triangulation is seen as a powerful way to bolster the validity of research or evaluation findings, as it is a strategy that aids in the elimination of bias and allows for the dismissal of plausible rival explanations through independent assessments of the same phenomenon (Campbell & Fiske, 1959; Greene & McClintock, 1985; Mathison, 1988). Through the use of multiple bibliometric indicators and interview data, the current study was able to provide a multi-faceted view into the effects of participation at an IDR center that a single approach could not as easily achieve. Further, as there are currently no widely accepted definitive indicators to measure IDR (Morillo et al., 2001), the use of multiple indicators for this measure (i.e. disciplinary participation, frequency, and diversity) appears to be a salient aspect of the evaluation design.

Triangulation of data is not only useful when the data from different sources is convergent, but also when it is contradictory, as was the case with the least successful case participant in the study. According to Patton (1980), “There is no magic in triangulation. The evaluator using different methods to investigate the same program should not expect that the findings generated by those different methods will automatically come together to produce some nicely integrated whole” (p, 330). The goal, he says, is to study the data as presented and understand why there are differences. Although bibliometric indicators pointed to Participant 1 as one of the participants whose publication and collaboration behaviors had changed the most after affiliation with the working group, interview data provided a direct contradiction to this conclusion. Analysis of interview data revealed, among other things, that the changes found in the bibliometric study were due to projects Participant 1 was working on outside of the group.

Although the current methods were valuable for evaluating the scope of the impacts on participant publication and collaboration behaviors as a result of affiliation with an IDR group, the methods could be further refined to provide more useful information (see next section "Implications for Future Research" for a more detailed discussion). For instance, I and S scores appear to be a promising metric for evaluating researcher interdisciplinarity, but perhaps the whole group-aggregated pre-post design is not the most appropriate for using these metrics in this setting. It is possible that a multi-level modeling approach to examining changes in these metrics within researchers grouped by various diversity indicators (e.g. career stage, group affiliation, age, disciplinary affiliation) might provide a clearer picture of patterns in changes in these scores.

Implications for Future Research

Future research to extend and expand the current study would be valuable to stakeholders at both the center and federal levels. Incorporation of a non-equivalent no-treatment control group of researchers who applied for, but did not receive, support for working group applications, would increase the internal validity of the study (Shadish et al., 2002). The inclusion of such a control group would add to the interpretability of the results, allowing readers to determine whether or not observed changes are more likely attributable to center affiliation, or to underlying environmental or maturational changes (Garner et al., 2012).

Extending the time period of the study would provide a more comprehensive view of the lasting effects of center affiliation on participant behaviors. The time period for the present study was necessarily brief, as the center had only been in operation for four years at the onset of the study. However, as Chubin et al. (2010) noted in their evaluation of the NSF Science and Technology Center Integrative Partnerships (STC) Program,

> Behavioral change occurs over time…the effects of behavioral change may not occur until after the 10-year life of an STC…the effects, alternatively, may continue on after the STC ceases to exist as a formal entity, as faculty who participated in it continue to engage in the collaborative, interdisciplinary, cross-institution, and cross-sector professional activities first engendered by the NSF award (p. C-6).

Although immediate effects on participant collaboration activities were apparent in the current study, a longer time frame (one that incorporated both more pre and post years of bibliometric data) would provide a view of the sustainability of the effects of the center on participant behaviors.

Future research could also benefit from the addition of more participants. The present study examined the data available for 46 participants who had completed working groups, however, as more groups complete their cycles, new participants could be added to the study. Increasing the number of participants in the study would lend itself to a number of options for further exploration, including further investigation of the differences in gender experiences within working groups. Another interesting extension to the study would be to disaggregate participants by self-described field of study and relate this to the publication and collaboration outputs studied here. For instance, do those who consider themselves mathematicians experience greater changes in interdisciplinarity than those who consider themselves biologists by training?

Finally, future research could benefit from measures that quantify the value-added aspects of participating in a NIMBioS working group that were indicated by participants during the interview process. For instance, network analysis measures could be used to quantify the ways in which participants collaborate (beyond co-authorship) with other working group participants with whom they would not have interacted had they not been involved in the group. Included also in these value-added measures could be examining more closely novel co-authors and journals of publication at the individual participant level after affiliation to determine what changes are occurring to what degree and for whom.

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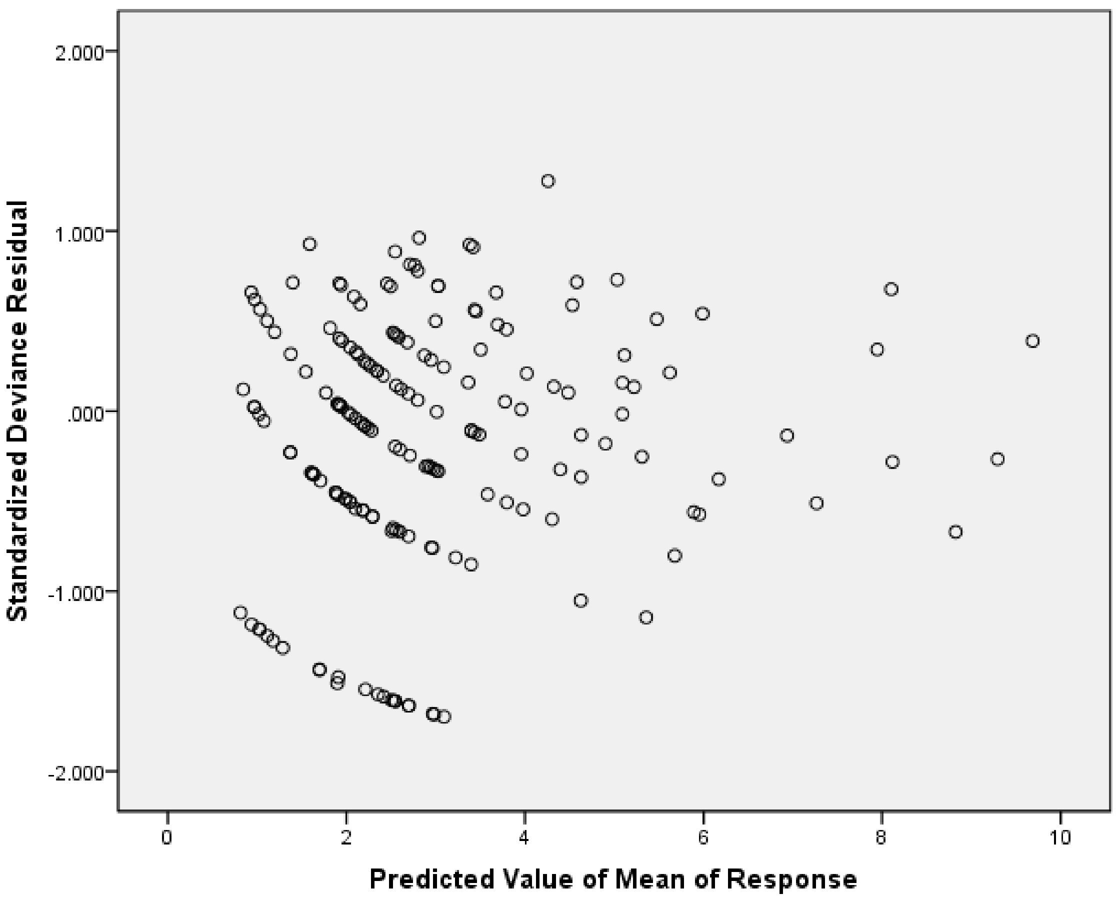
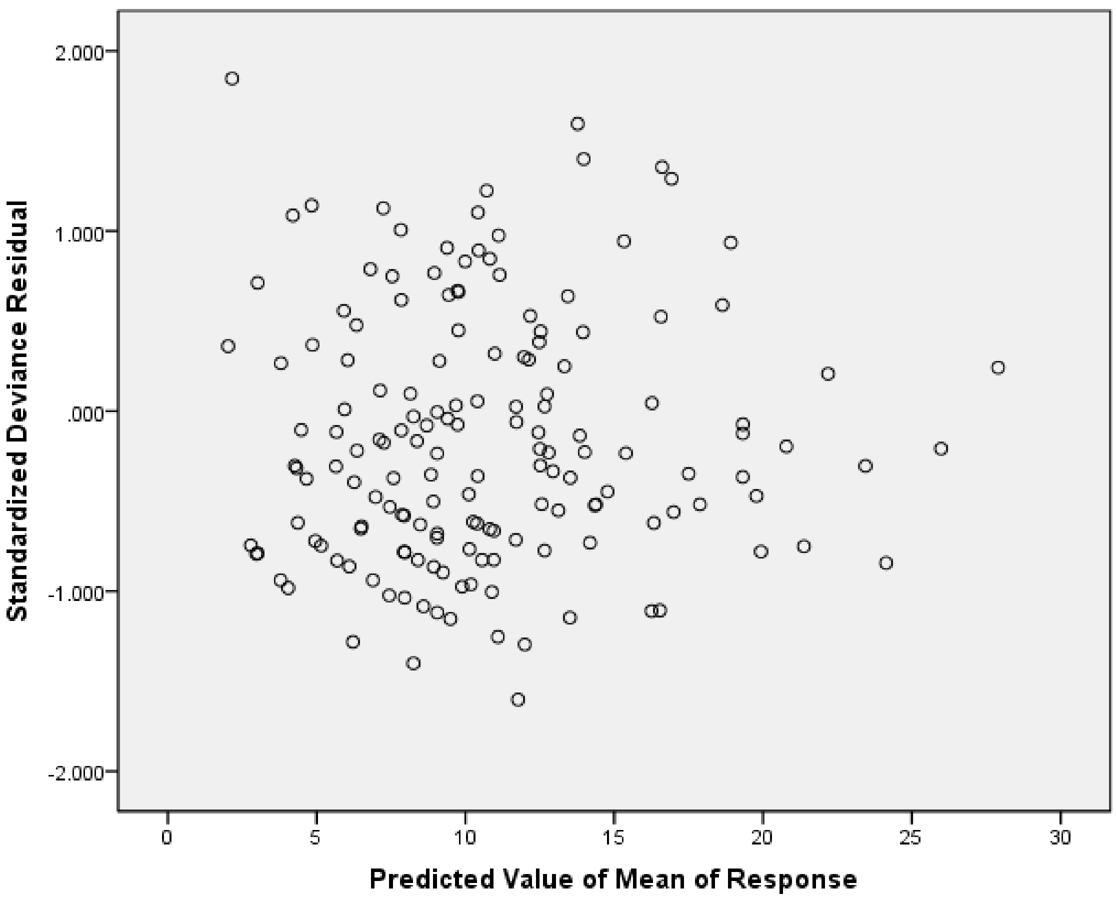
APPENDIX A

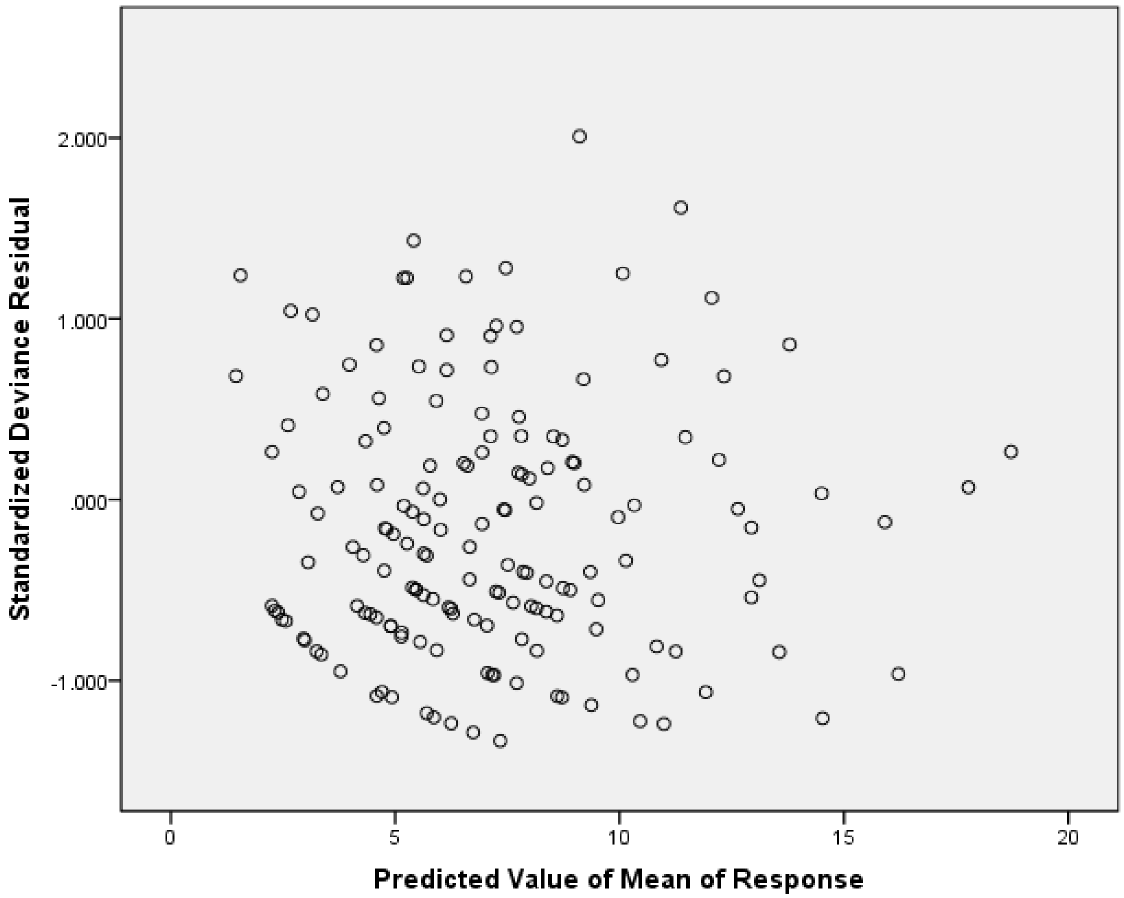
A1. Plot of residuals versus fitted values for regression model on participant products (Research Question 1)



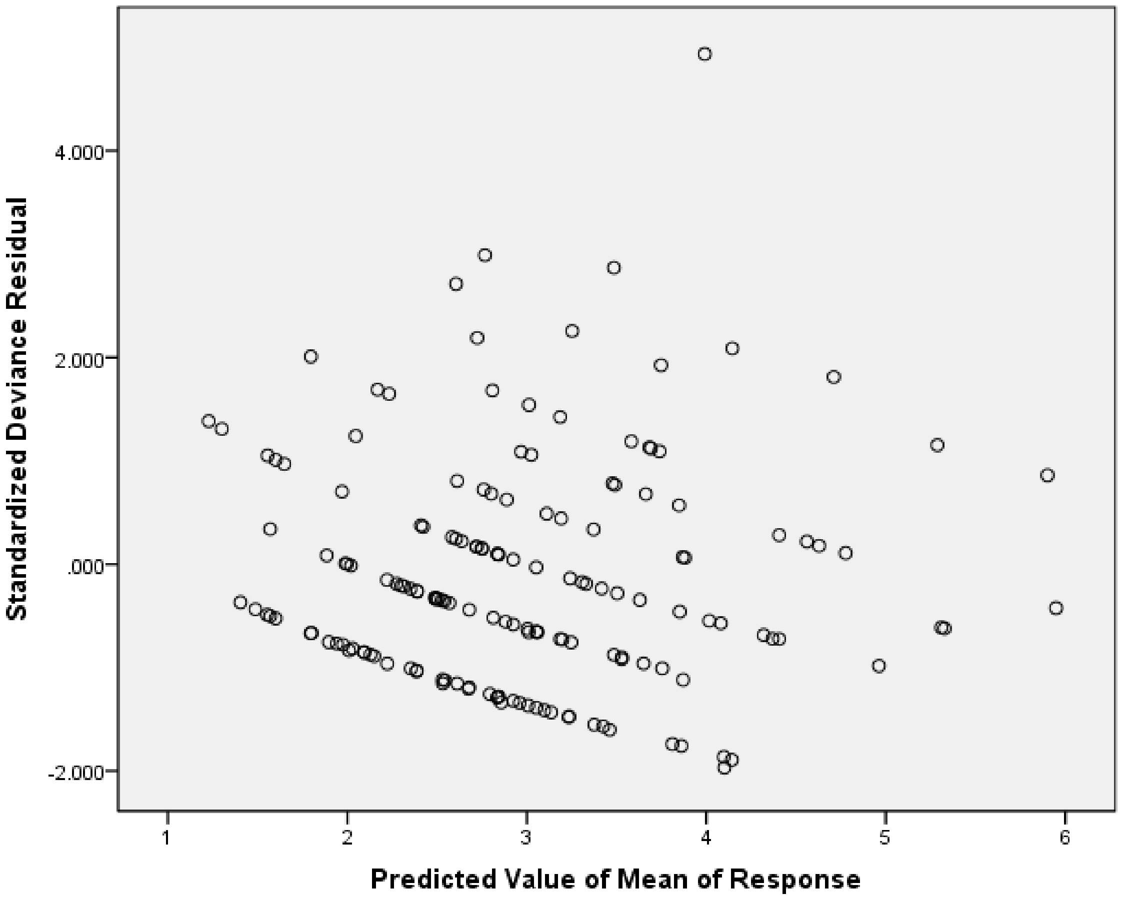
A2. Plot of residuals versus fitted values for regression model on number of co-authors (Research Question 2)



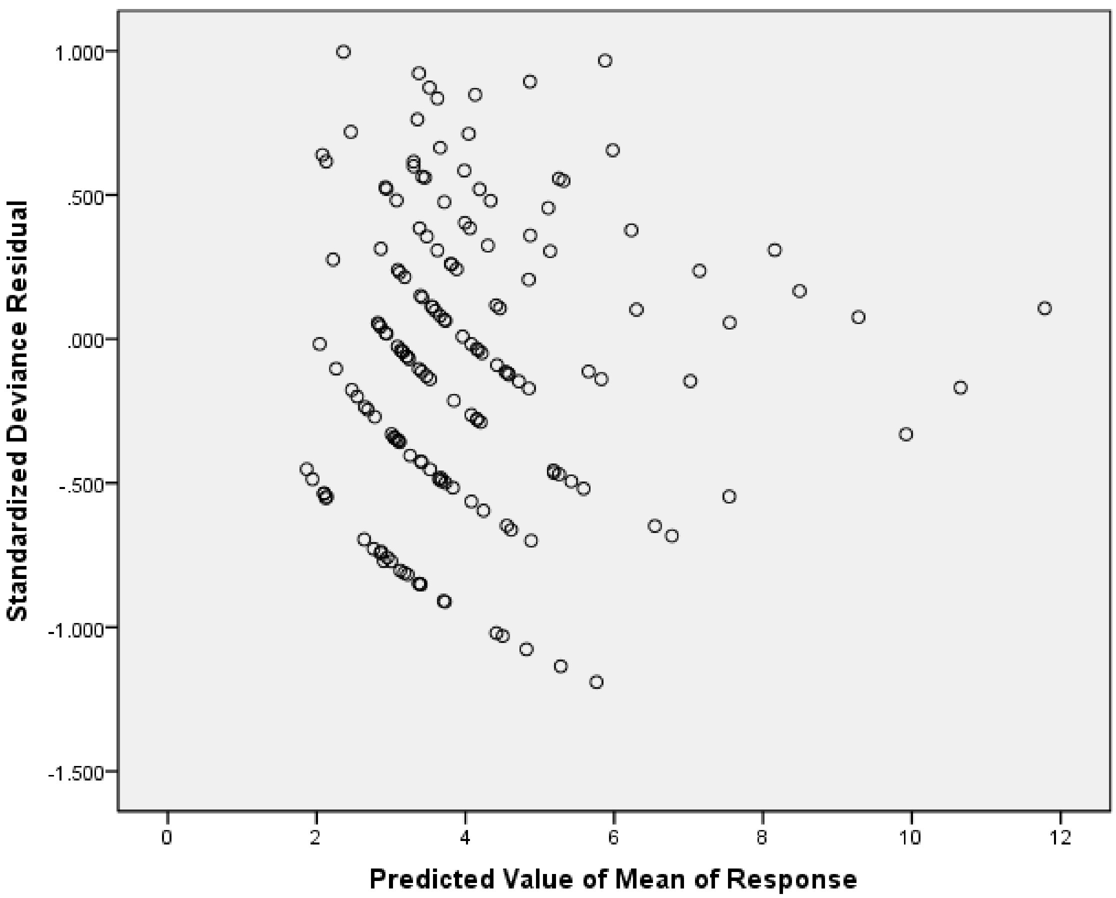
A3. Plot of residuals versus fitted values for regression model on number of cross-institutional co-authors (Research Question 2)



A4. Plot of residuals versus fitted values for regression model on number of international co-authors (Research Question 2)



A5. Plot of residuals versus fitted values for regression model on disciplinary frequency (Research Question 3)



APPENDIX B

Dear ______,

You are invited to take part in a research study that examines the effects of participating in a NIMBioS Working Group on academic publication and collaboration activities. A preliminary study comparing participant activities two years prior to affiliation with their Working Groups to their activities two years after initial affiliation identified your publication and/or collaboration activities as being one of the most changed (out of a pool of 46 participants from completed Working Groups) based on several measures. I am interested in talking with you to try to understand how (if at all) affiliation with your Working Group may have impacted these changes. This project is part of the overall evaluation of NIMBioS activities, and will also be used to fulfill part of the requirements of my doctoral degree in Evaluation, Statistics, and Measurement at the University of Tennessee. The project has been approved by the University of Tennessee's Institutional Review Board (IRB# 8820 B).

To collect the kinds of data I need to complete this research project, I would like to ask you a few questions about your experiences with your NIMBioS Working Group. If you agree to take part in this study, you will be asked to take part in a telephone interview lasting approximately 30 minutes. The interview will cover questions about why you became involved with the Working Group, benefits you may have gained from participation, factors that may have influenced your publication and/or collaboration patterns, and aspects of leadership and group structure that may have contributed to the results you have experienced.

Your interview responses will be confidential, and will not be shared with other members of your Working Group, the NIMBioS leadership team, or Advisory Board in a way that may identify you and your name will not be included in any oral or written report. Your participation in this project and answers to the questions asked will have no bearing on acceptance into future Working Groups or other activities at NIMBioS in the future.

There are no known risks associated with your participation in the project. If you choose to participate, a transcript of your interview will be sent to you prior to analysis for verification. A copy of the final report will also be shared with you upon completion.

If you have questions at any time about the study or the procedures, you may contact me at (865) 974-9348; or by email: pambishop@nimbios.org. If you have questions about your rights as a research participant, you may contact Brenda Lawson, Compliance Officer and IRB Administrator, UT Knoxville Office of Research, Phone: (865) 974-7697; Email: blawson@utk.edu.

Thank you for your consideration. I do hope that you will agree to assist us in our efforts, fully supported by the NIMBioS Leadership Team and our sponsors, to evaluate the impacts of NIMBioS on interdisciplinary research and education. If you would like to participate, please respond to this email indicating your agreement and to set up an interview time during the month of July.

Best,

Pam

VITA

Pamela R. Bishop earned a Bachelor's degree in Plant Sciences (2000) and a Master's degree in Entomology and Plant Pathology (2004), both from the University of Tennessee, Knoxville. Pamela has worked as the state evaluator for the federally-funded Mathematics and Science Partnership program, as an external program evaluator at the Oak Ridge Institute for Science and Education, and currently holds an internal evaluation position with the National Institute for Mathematical and Biological Synthesis. She received her Ph.D. in Educational Psychology and Research in December, 2012 from the University of Tennessee, Knoxville. Her research interests include center-scale evaluation of federally-funded research and education programs, measurement and evaluation of interdisciplinary research, and network studies of researcher collaboration.