THE ROLE OF COST-SHARING AS A SIGNAL OF PROJECT QUALITY IN THE FEDERAL FUNDING OF ACADEMIC RESEARCH:
AN APPLICATION TO THE NATIONAL SCIENCE FOUNDATION

A Dissertation in
Economics

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ABSTRACT

One of the traditional justifications for the use of cost-sharing in the federal funding of academic research is an equity argument. Since universities accrue real, monetary gains from research, either directly from the generation of patent revenues or indirectly from the gaining of increased prestige that translates into increased tuition revenues or more external research funding, they should be required to pay their fair share of the costs. The focus of this thesis is to explore another potential justification for the use of cost-sharing, that cost-sharing provides information to the funding agency about the quality of the proposal. A theoretical model is developed to establish a framework for understanding the cost-sharing element in the federal funding of academic grants. The model predicts that in some funding environments, cost-sharing would allow the agency to weed out low type projects, leaving only high type projects in the proposal competition. Under looser agency budget environments, lower type projects could apply and be funded, but higher cost-sharing commitments would be required from all proposals which had lower preliminary assessments.

In testing these predictions, the empirical model employed data on 1168 continuing grants that were funded by the National Science Foundation between 1993 and 2000. The results provided very minimal evidence that cost-sharing varies negatively with the preliminary assessment. This evidence includes results from the 1993-1994 and 1997-98 periods, results from the individual NSF directorates, and the relationship between total cost-sharing and grant award. Thus, we cannot conclude with any certainty that there is any informational content in the cost-sharing level. However, the testing did show that greater cost-sharing is a function of the threshold of the project, whether this threshold derives from the university, department, or researcher level characteristics. This is supportive of the traditional leveraging explanation of cost-sharing. Agencies seem to act in a manner similar to that of a price-discriminating monopolist, requiring varying levels of cost-sharing (or “prices”) based on the ability of the proposer to provide cost-sharing. It was also found that cost-sharing was affected by the agency’s threshold, which varied over time and across field or directorate.
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Scientific research and the resulting advancement of technology and knowledge is the fundamental basis for the advancement of society. In the United States, academia has held a prominent role in research and development, and the federal government has been a significant sponsor of these activities. Because of the public good nature of scientific research, basic fundamental research in particular will be underperformed in the private marketplace. The role of universities in carrying out this research for society is an integral part of the notion that there is a social contract between the federal government and U.S. universities. For reasons that will be described below, universities have increasingly been asked to pay for a larger part of this research in the form of cost-sharing requirements. The examination of the role of this cost-sharing component of academic research funding is the focus of this dissertation.

There have been many attempts at modeling the overall behavior of universities (e.g. Garvin, 1980; Southwick, 1967; Kesselrig & Stein, 1986). These models treat the university as a utility maximizing agent, whose choice variables are the outputs of an educational institution, such as levels of teaching and research. But when looking at the models describing the process of research funding, the literature is much sparser. Of the papers that have been written on this

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1 In 2006, of the $47.8 billion spent on U.S. university research and development, 62.9% came from federal government sources for a total of $30.0 billion. The remainder was made up of internal funding (19.0%), state and local government funding (6.3%), industry funding (5.1%), and funding from other sources (6.7%).
topic, all have focused on a specific aspect of the funding process. Connolly (1994) shows that the relationship between a university’s level of external research funding and its internal research support is a dynamic one. In other words, a university’s decision about research support in one period will positively affect the level of external grants awarded in future periods. Lazear (1997) describes a two period overlapping generations model which looks at the effort levels supplied by young and old researchers. He shows that these effort levels can be increased by manipulating the characteristics of the award structure, such as lessening the number of awards, but increasing their size or making awards contingent on the age of the researcher. Finally, the model presented in Arora and Gambardella (1997) is a two period model of industry funding of academic research. They demonstrate that industry is less likely to gamble on funding young, unproven researchers than federal agencies because the individual firm is not guaranteed of being able to hire the researcher again in the second period if the researcher is determined to be very productive.

The shortcoming of the current literature is that it does not present a complete model of the interaction that occurs between individual research universities and the agencies that fund a large percentage of their work. Like universities, the agencies are utility maximizing entities\(^2\), but in the above three models, their choices are largely ignored. By making the agency behavior exogenous, the models boil down to the university (or researcher in the case of Lazear) maximizing utility subject to the given policies of the agency. For example, in Connolly, the

\(^2\) Agency payoff is increasing in research output, which will be defined in section 2.2.
level of research grants in period t is solely a function of internal research support in the prior period. This dissertation proposes a game theoretic approach to the federal research funding process. This will entail the modeling of a framework that allows both the university and the funding agency to make decisions that represent their best interests. The main feature of the model will be the use of cost-sharing as a signal to the funding agency about the potential productivity of the proposal.

Cost-sharing, in the context of academic research funding, is defined as the portion of the cost of a federally funded research project that is still paid by the university. This university component could come in the form of direct dollar contributions to the project or in-kind contributions towards the project. For the National Science Foundation, these in-kind items could be goods or services specifically identifiable to the NSF sponsored activity, including such items as the use of university facilities to conduct research, unfunded time spent by the researcher or staff on the project, or the donation of supplies (National Science Foundation, 2008d). Prior to the implementation of the 1999 Presidential Review Directive (NSTC, 1999) that drastically reduced the role of cost sharing in the funding process, the use of cost sharing had been growing in importance. Feller’s 1997 study on the cost-sharing experiences of U.S. universities highlighted this trend. In a national survey of university administrators, 81% reported having encountered a NSF program announcement that contained cost-sharing percentage requirements. Although this number varied across federal agencies, it was usually at least 60%. In addition, the majority of respondents cited the increasing use of language in proposal guidelines which “suggests”, “requests”, or “encourages” cost-sharing. Thus, even when specific requirements were not set,
universities often cost-shared voluntarily because of the increasing pressure to present a competitive proposal. The theoretical model developed in chapter 2 suggests that this motive may be associated with proposals that are lacking in some area. For example, the principal investigator may have a weak track record or the department’s facilities are not up to date. Finally, even after a proposal was given pre-approval based on the initial review, negotiations could occur between the agency program officer and university officials or the individual investigator about cost-sharing levels. This increasing prevalence of cost-sharing practices was opposed by the Association of American Universities, and it was backlash from this group and others that led to the 2004 decision by NSF to further curtail cost sharing beyond what was called for in the 1999 Presidential Review Directive (Field 2004). However, in August 2007, the National Science Foundation was given the task of reevaluating the 2004 changes with the passage of the America Competes Act. The first National Science Board report that came in response to this Congressional action made several recommendations, most notably the reinstatement of cost-sharing in award competitions that previously involved significant cost-sharing levels. These included large programmatic awards and awards involving university/industry partnerships. The Board also plans to release another report in the second half of 2008 offering further recommendations with regard to the wider use of voluntary cost sharing (National Science Foundation 2008b).

Because of the significance that cost-sharing once had and may have again, examining its role is critical to understanding the whole academic research funding process and what effects it was having on the university-government relationship. The government has a long history of
providing support for scientific research. As described in Butos & McQuade (2006), projects such as the electric telegraph and Lewis & Clark’s expedition were beneficiaries of federal funding. During the two world wars, a significant portion of government-sponsored research centered on defense projects. In 1945, the Office of Scientific Research and Development issued a landmark report that laid out a national policy with respect to the support of scientific research and education. This led to the creation of the National Science Foundation and solidified the notion of a social contract between government and academia. In the 1990’s, the increasing implementation of cost-sharing requirements and expectations by federal agencies was seen as eroding this traditional relationship.³

It has been suggested that one of the reasons agencies increasingly relied on cost-sharing as a factor in the award process is that it served as a signal to them about the potential productivity of the researcher and the value of the proposal (Feller, 1997). In other words, if the university is willing to make a commitment to the project with its own funds, it must be fairly confident of the project reaping future rewards, whether this is in the form of revenue streams from patents or prestige from making important scientific advances.⁴ However, if cost-sharing is to be an informative signal, it must be the case that agencies can deduce the level of productivity based on the observed levels of cost-sharing (i.e. there is a separating equilibrium). If this is not the case,

³ For more on this social contract, see (Guston & Keniston, 1994) or (Brooks, 1993).

⁴ Also, current levels of cost-sharing may be an indication to the agency of the university’s commitment to a specific field or research area. This institutional commitment is especially important to the long term success of an individual’s research program or large programmatic awards.
then it is possible that an alternative motive for cost-sharing is more relevant. Connolly (1994) also refers to the concept of signaling, but this time at the university level. It demonstrates that greater university-wide funding of research can serve as a signal of high quality research at the university, which increases external funding.

The traditional justification for the federal funding of research is based on the public good aspect of research and development outputs. If research activities are left to the free market, not enough R&D will be performed. However, since universities clearly reap private benefits from research (e.g. prestige, profits from patents), cost-sharing was seen as a method for the agency to shift the part of the cost that corresponds to these private gains to the university (Feller, 1997). In other words, the agency is attempting to extract some of the producer surplus from the university. This was the commonly accepted rationale for cost-sharing. This explanation for cost-sharing is based on the premise that agencies have good information about the value of the project to the university. If this is the case, then the amount of cost-sharing required by the agency can be described as an application of the model of non-linear pricing by a monopolist. When a monopolist knows the consumer’s utility function, can offer the product for sale at varying prices, and can restrict resale of the product, it can offer the product at such a price that will extract a maximum level of surplus from each consumer (Kreps, 1990). When an agency issues grants at varying cost-sharing levels, this is analogous to a firm with market power selling a product at varying prices. Clearly “resale” is not an issue for the funding agency, as scientific work must be performed by the researchers described in the proposal. Thus, if rather than having incomplete information as is suggested in chapter 2, the agency knows the true value of the
project to the university, all three of the criteria for price discrimination are satisfied and the resulting cost-sharing level may best be described by the traditional leveraging explanation. When empirical tests are performed in Chapter 3, the finding of significance of variables related to the researcher’s ability and willingness to pay for the project would be support for this cost-sharing motive. For some examples of industries with 1st-degree price discrimination, see Goldberg’s (1996) description of new car sales, Ulph & VulKan’s (2000) description of e-commerce sites, or Rothschild & White’s (1991) description of university tuition pricing. Phlips (1983) contains an overview of the origins of price discrimination theory and its relationship to standard price theory.

Chapter 2 of this dissertation is concerned with the development of a theoretical framework that can be used to analyze this one-shot game played between the agency and grant applicant. As this game is an example of an incomplete information game in which the party with more information moves first and the second party responds to this message, it follows the general framework described in the signaling literature. The seminal article introducing the notion of signaling is Spence’s 1973 job market signaling model (Spence, 1973). In this model, there are high and low productivity workers that could be applicants for a job. The employer cannot observe the true type of the applicant, but it can observe the educational level attained. Spence assumes that the level of education does not impact the workers productivity. However, the wage offered to the applicant is increasing in this educational level. In this environment, one possible outcome is that both low and high types will find it worthwhile to expend the costs.\footnote{These costs may include psychic costs, the cost of time, as well as monetary costs.}
necessary to attain a high level of education and receive the higher wage offer (i.e. there is a pooling equilibrium). In this case, education is not an effective signal. However, if it is the case that the marginal cost of attaining the high level of education is greater for the low types than the high types, it may become too expensive for the low types to mimic the high types. In this case, observing a high level of education signals to the employer that the worker is highly productive and a higher market wage needs to be offered to retain their services. This crucial assumption that \( C_e(L,e) > C_e(H,e) \) is necessary for a separating equilibrium to result. Also known as the single crossing property because the utility function of the low type is steeper than that of the high types (see Figure 1.1), this basic assumption is key to the existence of a separating equilibrium in a variety of signaling contexts. The cost-sharing model that will be presented in chapter 2 is no exception. It will be shown that low type proposals will not be able to include as high of a level of cost-sharing as high type proposals.

Spence’s paper spawned the application of this signaling concept to many contexts. For example, Myers and Majluf (1984) used this approach to facilitate a better understanding of the corporate issuance of stock to finance an investment project. Because of the lack of complete information about the firm’s value if the project was undertaken, potential investors may under-invest. The firm’s owners, who know more about the value of the company, send a message to investors through the equity stake that is offered. Under some conditions, a pooling equilibrium may allow the funding of both low and high types, but at a steep cost to the high types. They also
show that a separating equilibrium that favors the high type firms is not likely. Any equity stake level that produces separation will result in only the low types being funded. Therefore, valuable investment opportunities have difficulty raising funds in this manner and are forced to turn to other forms of financing, such as debt issuance or internal funding.

Kirmani & Rao (2000) presents an example of signaling in the marketing literature. In their model, firms try to signal product quality to uninformed customers through the use of marketing tools such as advertising, branding, and warranties. They show that a separating equilibrium, in which high quality products can differentiate themselves from low quality products, can be
obtained. In this case, the single crossing property is satisfied because low quality firms will not find it profitable to undertake these costly signals (they can’t recuperate the costs without repeat sales). In Milgrom & Roberts (1982), a monopoly is faced with a potential entrant that is unaware of the monopolist’s cost structure. They demonstrate that limit pricing can serve as an informative signal to the potential entrant that the monopolist has a low cost structure, thus deterring entry. For a further review of the signaling literature, see Kreps (1990).

Empirical tests of the hypothesis that cost-sharing can be an effective signal is the subject of Chapter 3. In light of the significant changes to agency cost-sharing policies that have been implemented, Chapter 4 will examine how the major players have been affected, summarize the results from the dissertation, and draw some conclusions.
CHAPTER 2
THE THEORETICAL FRAMEWORK

The general setup of this two player game is described in the following:

(i) The funding agency’s goal is to maximize total research output, which is equivalent to the advancement of scientific knowledge. For example, the National Science Foundation states its mission as the following: “To promote the progress of science; to advance the national health, prosperity, and welfare; and to secure the national defense.” In their FY 1999 GPRA Performance Plan, they state five outcome goals. Besides the promotion of research, goals include the promotion of the knowledge of the sciences, the development of a diverse scientific community, and the dissemination of information on the state of national and international science. Here, we will focus on the goal of promoting discoveries at the frontiers of science, which in terms of this model means the promotion of research output. In more measurable terms, this research output could be defined as the quantity and quality of patents or publications resulting from a research project. To accomplish this goal of maximum total research output, the agency will attempt to fund more projects at a lower level (a process known as “leveraging”). This will be achieved by incorporating a cost-sharing element into the funding process. At a minimum, the cost-sharing level must be large enough that the expected net benefit from the project equals some threshold level for the agency.
The university’s goal is to maximize its payoff from research, which is the difference between revenues resulting from research performed by the university and institutional cost-sharing contributions. Universities enjoy real monetary gains from the investment in research activities. These revenues may flow directly from the research project when valuable discoveries are patented. There may also be indirect monetary benefits that result from the accumulation of institutional prestige when research produces successful outcomes (James, 1990). For example, there may be increased tuition revenues. Garvin (1980) argues that greater prestige leads to a greater number of student applications. This has two positive impacts on university revenue. First, it increases the university’s pricing power, thus allowing greater tuition revenues. But there is a second impact, as selectivity increases, prestige rises, creating a positive feedback effect for the university. Another positive outcome of accumulating prestige is the increased ability to gain greater future external research funding. This of course also has a positive feedback effect, as landing a particular award or a coveted research center not only produces greater research output, but also increases the institution’s prestige, allowing it to garner more future awards and greater tuition revenues. Garvin and James both model this prestige level as a key factor influencing their overall objective, the maximization of university utility.

Although the origin of the concept of universities as prestige-maximizers goes back to Garvin’s 1980 book, recent research in higher education not only bolsters this notion, but extends it further. David Dill (2003) describes the “arms race for prestige” between universities competing

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6 Although universities have multiple objectives, the focus of the model is on the optimal allocation of a given institutional research budget to maximize the payoff from research.
for increasingly important reputational rankings in both the research and teaching arenas.

Others document the growing privatization of public universities (Feller, 2007) and the increasing collaboration between universities and industry (Bok, 2004). Dill goes as far to say that the “non-profit” label attached to the academic sector is no longer an accurate description as the seeking of revenues in excess of expenditures is a central goal. The reason that a “for-profit” label is not used is that profits are not distributed to owners or shareholders. Therefore, the generation of revenues from the creation of prestige seems to be an increasingly important motive for the undertaking of research activities.

The university must choose how to allocate its limited internal research budget among departments. This financial support might be at the departmental level (e.g. funding of new equipment or reduction in teaching loads) or might be designated towards a specific project in the form of cost-sharing. For individual research proposals, the constraint placed on the university is that the net benefit from the research (i.e. the revenue from the research output minus the cost-sharing component) must exceed some given threshold value for the university.

The exact specification of the game will depend on the timing of the cost-sharing stage in the overall funding process. As alluded to in Chapter 1, there are three different phases of the funding process where cost-sharing can take place. Cost-sharing requirements could be specified in the program announcement, it may be voluntarily offered by the university in an attempt to make the proposal more attractive to the funding agency, or it could be the result of a pre-award budget negotiation process. A basic model will be developed that will allow for voluntary cost-
sharing above the level required in the program announcement, but assumes no pre-award bargaining stage. This streamlined version of the model yields insights about the funding process that will be the subject of the empirical testing in chapter 3. A more general model that allows for cost-sharing to occur at any or all of these three stages is included in the Appendix.

2.1 Basic Assumptions

Before proceeding into the details of the model, it is important to point out the basic assumptions that are being made about the whole funding process. First, the game that will be described in the remainder of this section is only one part of a larger game that is taking place. There is really a third player involved, the federal government. The legislative and executive branches of the federal government determine the agency budgets and the Office of Management and Budget sets specific regulations on agency cost-sharing policies. It is within the constraints of these federal decisions that the funding agencies operate. There is also direct interaction between the universities themselves and federal lawmakers through lobbying efforts. The use of political pressure can be an effective tool in altering the rules of the game they play with the agencies. Another complexity not considered in this dissertation is that there are multiple levels of decision-makers within a given university. Individual investigators make decisions about which grants to seek and it could be either the department or the university administration that provides the cost-sharing. Because there are often conflicting goals at each of these levels, it is often more accurate to describe the game as one between these separate elements and the agency involved. For example, it could be the case that the principal investigator colludes with the
agency program officer during cost-sharing negotiations with the university administration (Feller, 1997). In an attempt to focus on the cost-sharing aspect of the research funding problem, these intra-organizational complexities, as well as the “larger game”, will be mostly overlooked in the remainder of this dissertation.

Note also that in the remainder of the theoretical model, the agency is treated as a monolithic decision-maker. In reality, there are multiple actors within the agency that play a role in the funding decision. At the National Science Foundation for example, the program officer is central to the decision-making process, but relies on at least 3 external experts who review the proposal. These reviewers are charged with the task of answering 2 primary questions: “What is the intellectual merit of the proposed activity?” and “What are the broader impacts of the proposed activity?” The reviewers submit a review score based on a 5 point scale along with written comments. The program officer synthesizes this feedback from reviewers with other information about the proposal and makes the funding decision. The Division Director reviews all program officer decisions. For exceptionally large awards, there are further review mechanisms (National Science Foundation, 2007). Although the exact proposal review mechanism varies by agency, the use of multiple evaluators of proposals is common. For example, the National Institute of Health assigns the proposal to a closely associated center of study, e.g. the National Cancer Institute, where it is subject to review by a standing committee. This committee evaluates the proposal and decides on funding based on five criteria: significance, approach, innovation, investigator, and environment. Thus, the assumption of a single decision-maker at the agency needs to be made regardless of the agency. It should be noted that although the basic theoretical
model is general to the basic federal funding process for research awards, the National Science
Foundation is the focus of the dissertation and will be the only agency examined in the empirical
model of Chapter 3.

2.2 Setup of the Game

Define the proposal’s type as:

\[ T = f (M, A, SD) \]  \hspace{1cm} (2.2a)

where M is the scientific merit of the project, A is the researcher’s ability, SD is the state of the
department, and T is increasing in all three arguments. This equation submits that besides the
quality of the proposal, the natural ability of the researcher and the characteristics of the
department (such as quality of colleagues and facilities, teaching loads of faculty, numbers of
post docs & graduate students, etc.) will play a role in determining the research output flowing
from a project.\(^7\) Since M, A, and SD are exogenous to the model, equation 2.2a is included here
only to motivate why T is unobservable to the agency (see below).

Stage 0: Nature draws a single proposal of type T from the distribution \( p_i(T) \), where i

 corresponds to department i. For simplicity here, assume that the type drawn is either high

productivity (\( T_H \)) with probability \( p_i \) or low productivity (\( T_L \)) with probability \( 1-p_i \). The

subscripts on these probabilities imply that the state of the department and the quality of faculty

\(^7\) See (Ellyson & Krueger, 1980), (Muffo & Coccari, 1982), (Wolfe, 1982), (Hare & Wyatt, 1988) & (Kosha,
Kosha, & Gupta, 1996) for discussion and empirical testing of the factors that influence research output.
within that department will play a role in determining the chance of drawing the high or low type researcher.

**Stage 1:** The university observes the productivity of the project (i.e. knows the type drawn in stage 0) and chooses the level of cost-sharing, C. The university’s basic problem can be written as:

\[
\begin{align*}
\text{Max } & \Pi[\Psi(T)] - C \\
C & \\
\text{subject to } & \Pi[\Psi(T)] - C \geq X_U \\
& G > C \geq C \\
& \Psi[E(T|C)] - (G-C) \geq X_A
\end{align*}
\]
where $\Psi$ is the function that relates productivity into research output and $X_U$ is the university’s threshold level which much be exceeded.\textsuperscript{8} The last constraint represents the agency’s participation constraint. The intuition behind this and the notation will be discussed below in stage 2. As mentioned earlier, research output can be abstractly defined as the advancement of scientific knowledge or more concretely defined as the end product of the research project, such as a patent, a publication, or the revenue generated from the sale of scientific knowledge. It is from these that the university benefits, as is shown in the revenue function $\Pi$ which translates research output into the monetary rewards from the project (where $\Pi_T > 0$). A value of $X_U$ greater than zero implies that the university will never offer a level of cost-sharing such that the net benefit from research is negative. The use of a threshold level here is intended to capture the idea that universities face a research budget constraint. With this threshold value, some projects may not be backed by the university even though they would yield positive net benefits. We can also infer that this threshold value will be higher for universities facing tighter research budget constraints, implying these universities can only afford to fund the relatively higher quality research. However, if a university has an abundance of resources, they can afford to fund a wider range of projects (i.e. the threshold is lower).

Finally, note that the potential use of cost-sharing requirements in the program announcement is incorporated into this model by providing a lower bound on the level of cost-sharing. In other

\textsuperscript{8} In models of overall university behavior (Garvin, 1980; Southwick, 1967; Kesselrig & Stein, 1986), both research and teaching enter the utility function. From this, an optimal level of teaching and research can be found. So implicit in the setup here is this fixed amount of money that has been allocated towards research (the threshold level is derived from this total research budget). In order to reach quantifiable conclusions that can be tested in chapter 3, it is assumed that university utility is based solely on the revenues earned from the research output (given by the $\Pi$ function) less cost-sharing. Therefore, their problem simplifies to maximizing this net benefit.
words, instead of C coming from the interval [0,G], it is chosen from [C,G].

Stage 2: The funding agency receives the grant proposal along with the cost-sharing offer from the university. It does not observe the project type, but it does know the distribution from which it was drawn (i.e. it knows the prior probability that T = T_H equals p and that T = T_L equals 1-p). It also observes the university’s threshold level and payoff function. At first glance, it may seem odd to assume that T is unobservable because of the volume of information asked about the researcher in a grant application, the use of a merit review process, and the existence of departmental rankings. However, there are several reasons to expect that the true type is not known with certainty. First and foremost, with the exception of the merit review score, the agency’s information is based on factors that may quickly change. For example, the quality of complementary resources could diminish quickly if university (or department) budgeting priorities move away from a particular department (or research subfield). This could lead to increases in teaching loads, deterioration in quality of facilities and equipment, and reductions in graduate students and support staff. Another complementary resource that could change rapidly is the quality of research colleagues. Agency determination of department rankings may not take into account recent changes in faculty. For example, the quality of colleagues could quickly change if just a couple of key related researchers entered or left the department. To the extent that agency determination of department faculty is based on infrequently published

---

It is assumed here that this statutory cost-sharing, C, is exogenous to the model. It may depend on what type of grant is being funded, e.g. infrastructure awards tend to have higher levels of statutory cost-sharing. It might also depend on the current funding rules handing down to the agency from the Office of Management and Budget. In order to analyze the effects of differing values for C, 3 cases are addressed in section 2.3.
national rankings\textsuperscript{10}, these changes to department faculty could lead to inaccurate judgment of the true state of the department. In addition to uncertainties which exist about the current state of the department (SD), in the case of a young researcher without much track record, A is unknown, leading to greater uncertainty about type T. Therefore, because of uncertainties about the university’s future commitment to a department (or the department’s commitment to a research sub-field) instead of knowing T with certainty, the agency knows $p_i(T)$. This reflects the general sense the agency has about the chance of a highly productive project coming from department i. In other words, when an agency receives a proposal, they assign some probability that the project will be successful based upon what information they have (scientific merit, what they know about the department, past success of researcher, etc.).\textsuperscript{11}

$X_u$ being observable to the agency is based on the idea that the agency has an understanding of the current budget constraint faced by the university. Finally, the university’s payoff function is assumed to be known and constant across all research universities. This assumption implies that all research universities derive the same level of benefit from the same level of research output. After receiving the proposal and assigning some probability that the project will be successful (based on the information available, e.g. the cost-sharing offer, scientific merit, departmental rankings, past researcher success, etc.), the agency can then determine if the “expected net benefit” from the research proposal exceeds the given quality threshold \textit{required by the agency}.

\textsuperscript{10} The National Research Council has periodically used survey techniques to assess the program faculty of departments in most fields of study. This survey was conducted in 1982 and then not again until 1993. See National Research Council (1995).

\textsuperscript{11} As with investigator-initiated awards, in the case of a proposal to fund a research center, the university can be the best judge about what long term commitment they plan to make to the center beyond the length of the award. This university commitment will determine the long run productivity of the center.
This “expected net benefit” can be expressed as:

\[
\Psi[E(T|C)] - (G-C)
\]  

(2.2c)

where \(E(T|C)\) is the expected value of the type given the signal, the university’s threshold, university’s revenue function and the distribution from which the type was drawn. \((G-C)\) is the portion of the proposal cost to be funded by the agency. The agency’s threshold level is some value \(X_A\), which is based on the current budget available to the agency. In years with an abundance of awards to make, the threshold may be lower and in the lean years of budget cuts, \(X_A\) may be increased. The size of \(X_A\) may also be dependent on the field of study, as funding certain fields may be a priority for the agency. A threshold value is used here, rather than assuming that all grants with positive expected net benefits are accepted, in order to incorporate the element of limited available agency funds. In especially lean years for the agency, even relatively high quality proposals may go unfunded.

2.3 Solving for the Equilibria

This section will be concerned with finding both pooling and separating equilibria in the static model in which there are only two types of proposals being submitted. To establish a specific perfect Bayesian equilibrium, one must show:

(i.) The action of the agency, which is to fund or reject the proposal, is a best response to the pair of strategies, \(C_H^*\) and \(C_L^*\), given its beliefs about type after receiving the cost-sharing message
(call this belief $u(T|C)$).

and

(ii.) $C_H^*$ and $C_L^*$ are best responses to each other and the agency’s optimal strategy, given $u(T|C)$ for all possible cost-sharing levels.

It will be shown that the resulting equilibria will depend on characteristics of the university (i.e. its payoff function, threshold value, $X_U$, and miscellaneous observable characteristics that affect the distribution from which type is drawn), the characteristics of the agency (i.e. its threshold value, $X_A$), and the amount of the grant being offered ($G$).

Before proceeding, a number of definitions will be laid out:

\[
C_{H}^{\text{MAX}} = \Pi[\Psi(H)] - X_U \\
C_{L}^{\text{MAX}} = \Pi[\Psi(L)] - X_U
\]  

where $C_{H}^{\text{MAX}}$ and $C_{L}^{\text{MAX}}$ are the values of $C$ in which the participation constraints for the high and low type applicants hold with equality.

The participation constraint for the agency, in terms of $C$, is given in the following inequality:

\[
C \geq X_A - \Psi(T) + G
\]  

Thus, for a high type applicant, the value of $C$ in which 2.3c is just binding is:
\[ C_{AH}^{\text{MIN}} \equiv X_A - \Psi(H) + G \quad (2.3d) \]

and for the low type applicant, it is:

\[ C_{AL}^{\text{MIN}} \equiv X_A - \Psi(L) + G \quad (2.3e) \]

We can also conclude that it is always the case that \( C_{H}^{\text{MAX}} > C_{L}^{\text{MAX}} \) and that \( C_{AH}^{\text{MIN}} < C_{AL}^{\text{MIN}} \).

Figure 2.1 shows the three possible general cases that might occur, depending on the size \( C_{AH}^{\text{MIN}} \) in relation to \( C_{H}^{\text{MAX}} \) and \( C_{L}^{\text{MAX}} \).

It is assumed that \( C \) is fixed at a low level. This assumption, although consistent with the 1% statutory requirement used frequently in program announcements, will be relaxed in the appendix.
FIGURE 2.1

Case 1

Case 2

Case 3
2.3.1 Case 1: $C_{AH}^{MIN} < C_{L}^{MAX}$

Before describing the solution to this first case, one more definition is required. Define:

$$C_{A} = p \ C_{AH}^{MIN} + (1-p) \ C_{AL}^{MIN}$$  \hspace{1cm} (2.3f)

$C_{A}$ is the level of cost-sharing that just satisfies the agency’s participation constraint when type is unknown. In other words, this is the level of cost-sharing that they would expect to satisfy their participation constraint with equality when there are $p$ percentage of high types. If beliefs about type are unchanged after receiving the cost-sharing message, i.e. $u(H|C) = p$, but $C < C_{A}$, then the project will not be funded. Funding proposals with those levels of cost-sharing would mean the agency is violating its participation constraint.

Finally, before proceeding, note that because of complete information about the agency, rational researchers will not submit proposals that will violate the agency’s participation constraint and result in the rejection of funding. This implies that there is a 100% acceptance rate. This corresponds to the empirical model in Chapter 3 that uses data on funded proposals.

**Proposition 2.1**: If $C_{A} \leq C_{L}^{MAX}$, $C_{H}^{*} = C_{L}^{*} = C_{A}$ is a pooling equilibrium for Case 2.3.1.

**Proof**: If the levels of $C_{AH}^{MIN}$, $C_{AL}^{MIN}$, and $p$ are such that $C_{A} \leq C_{L}^{MAX}$, both types will offer cost-sharing equal to $C_{A}$ and be funded. This is the lowest cost-sharing level that satisfies both the
agency’s and university’s participation constraints. Agencies would be willing to fund high types at a lower cost-sharing level, but with an offer of $C_A$, prior beliefs about type are unchanged. High types could only be identified as such by offering greater than $C_L^{\text{MAX}}$, but this would not be preferable to $C_A$ since $C_A \leq C_L^{\text{MAX}}$.

For given values for $C_{A_H}^{\text{MIN}}$ and $C_{A_L}^{\text{MIN}}$, the level $C_A$ will be higher for lower levels of $p$. Intuitively, this means that the lower the probability of high type given the agency’s preliminary information, the greater the cost-sharing offer must be to induce the agency to fund the project. Also, note that for a given $p$, $C_A$ can be higher for higher levels of $C_{A_H}^{\text{MIN}}$ or $C_{A_L}^{\text{MIN}}$. From observing 2.3d and 2.3e, we see that this implies agency minimums will rise when the agency’s threshold increases, the grant amount increases, or the research output for the project falls. As $C_A$ rises, the equilibrium cost-sharing will continue to rise. However, after $C_A$ surpasses $C_L^{\text{MAX}}$, the agency can update its belief of type to $u(H|C) = 1$. This situation is addressed in proposition 2.2.

**Proposition 2.2:** If $C_A > C_L^{\text{MAX}}$, there is a separating equilibrium for Case 1 in which $C_H^* = C_L^{\text{MAX}} + \varepsilon$, where $\varepsilon$ is a value trivially larger than zero, and low types do not apply.

**Proof:**

When $C_A > C_L^{\text{MAX}}$, an offer of $C_A$ is no longer required to meet the agency’s participation constraint because any offer greater than $C_L^{\text{MAX}}$ allows the agency to update its belief from $u(H|C) = p$ to $u(H|C) = 1$. Rather, any offer greater than $C_{A_H}^{\text{MIN}}$ is now sufficient. Since Case 1
assumes $C_{AH}^{MIN} < C_{L}^{MAX}$, an offer $C_{H}^{*} = C_{L}^{MAX} + \varepsilon$ is the lowest offer that satisfies the agency’s participation constraint. Deviating to a lower offer below $C_{L}^{MAX}$ would be preferable to the high types, but such an offer would no longer allow them to be distinguished from low types, and thus would not be sufficient for funding.

2.3.2 Case 2: $C_{AH}^{MIN} > C_{L}^{MAX}$

**Proposition 2.3:** If $C_{AH}^{MIN} > C_{L}^{MAX}$ as in Case 2, there is a separating equilibrium in which $C_{H}^{*} = C_{AH}^{MIN}$ and low types do not apply.

**Proof:**

When $C_{AH}^{MIN} > C_{L}^{MAX}$, it is no longer sufficient for high types to offer only enough to distinguish themselves from the low types, i.e. $C_{L}^{MAX} + \varepsilon$ does not satisfy the agency’s participation constraint. Rather, $C_{AH}^{MIN}$ is the minimum required to induce funding. Since $C_{AH}^{MIN} > C_{L}^{MAX}$, low types do not apply as their participation constraint would be violated. High types cannot deviate to a lower cost-sharing level without violating the agency’s participation constraint and losing funding.

2.3.3 Case 3: $C_{AH}^{MIN} > C_{H}^{MAX}$

**Proposition 2.4:** If $C_{AH}^{MIN} > C_{H}^{MAX}$, neither high nor low types apply.

**Proof:**

The proof is trivial, since the agency will require at least $C_{AH}^{MIN}$, which is a greater amount than
either type would be willing to cost-share. This case will never occur in reality because it would imply that the agency would not fund any projects, which goes against its goal of maximum total research. Intuitively, what has happened is that the agency has no funds to award and thus has set its threshold so high that no applicant could ever meet the requirements.

2.4 Discussion and Summary of Results

Since Case 3 involves neither type applying, it will not be observed in real world data. This might result when the university has a small research budget, and thus an extremely high threshold level. Since these cases are not observed in the data, the discussion that follows will focus on Cases 1 and 2. Case 1 will be observed in environments in which budget constraints are relatively loose for both the university and agency, i.e. \( X_U \) and \( X_A \) are relatively low. This will lead to the agency cost-sharing requirements (\( C_{AH}^{MIN} \) and \( C_{AL}^{MIN} \)) being relatively low and university cost-sharing maximums (\( C_{H}^{MAX} \) and \( C_{L}^{MAX} \)) being relatively high. In Case 1, for funded proposals which would be observed in the data, the common link is that cost-sharing levels will be equal to the agency’s requirement \( C_A \), up to a maximum value of \( C_L^{MAX} \). So taking a closer look at this variable \( C_A \) will help us better understand both the nature of the funding game and allow us to derive some conclusions that can be tested using real world data on funded proposals.

Recall that \( C_A \) is defined as:

\[
C_A = p \ C_{AH}^{MIN} + (1-p) \ C_{AL}^{MIN}
\]
Substituting the definitions of $C_{AH}^{\text{MIN}}$ and $C_{AL}^{\text{MIN}}$ from (2.3d) and (2.3e) gives:

$$C_A = p [X_A - \Psi(H) + G] + (1-p)[X_A - \Psi(L) + G]$$

which can be rewritten as:

$$C_A = X_A + G - p[\Psi(H) - \Psi(L)] - \Psi(L) \quad (2.4a)$$

Performing a comparative statics analysis of (2.4a) gives intuitive insight into the equilibrium outcome and some testable conclusions that will be addressed in Chapter 3. First, and most interesting, is the relationship between $C^*$ and $p$. We find that since $\Psi(H) - \Psi(L) > 0$,

$$\frac{\partial C^*}{\partial p} < 0.$$  This is intuitively sound as $p$ represents the observable factors that the agency would use to predict type. When factors such as the track record of the researcher, the scientific merit score of the proposal, the quality of the department, and the stock of equipment are favorable, the agency will assign a high probability of the project being high type. This leads to a lower cost-sharing level that satisfies the agency’s participation constraint, and thus lower cost-sharing. In other words, proposals that appear to be of higher quality do not require the same level of cost-sharing commitment from the university to prove this quality level to the agency, or there is a tradeoff between cost-sharing and $p$. For proposals that are more questionable (i.e. have a low $p$), for example, proposals in which the scientific review score was in the middle range or the researcher has no track record, the cost-sharing amount would need to be higher to attain funding. This is consistent with the notion that the cost-sharing commitment by the
university can be a signal of the quality of the project.

Looking at the partial derivatives $\partial C^*/\partial G$ and $\partial C^*/\partial X_A$ also provide some interesting insights. We see that $\partial C^*/\partial G > 0$, which implies that cost-sharing levels will be increasing with grant size. So holding other factors constant, the greater the scope of the project, the greater the commitment that is expected from the university. We also see that $\partial C^*/\partial X_A > 0$, which suggests that more austere budgetary environments for the agency lead to higher cost-sharing levels being required. This is also intuitively palatable.

Finally, note that $\partial C^*/\partial \Psi(H) < 0$ and $\partial C^*/\partial \Psi(L) < 0$. This implies that as the research output from a project rises, less cost-sharing is needed to satisfy the agency’s participation constraint.

Case 2 will be observed in cases in which agency minimum cost-sharing requirements are relatively high (e.g. due to high $X_A$) and/or when university maximums are relatively low (e.g. due to high $X_U$). The equilibrium outcome in Case 2 showed that the cost-sharing level $C^*$ will equal the agency’s minimum amount required for the high types, i.e. $C_{AH}^{\text{MIN}}$. Again, performing a comparative statics analysis of $C^*$ will provide some insights and help in the understanding of the empirical results in Chapter 3.
Recall that (2.3d) gave:

\[ C_{AH}^{\text{MIN}} = X_A - \Psi(H) + G \]

From this we can see that the same relationships hold between \( C^* \) and \( X_A \), \( \Psi(H) \), and \( G \). The primary difference is that the variable \( p \) does not appear here as it did in Case 1. In this case, we found that low types were driven out of the proposal competition. As a result, the agency updated its belief to \( u(H|C) = 1 \). In other words, under these circumstances, \( p \) is fixed at 1 and no longer a variable. Thus, there is not the same tradeoff between preliminary agency information and cost-sharing that we saw previously. The proposal has been correctly identified to be a high type proposal. Intuitively, this means that the proposer does not need to use cost-sharing to demonstrate the university’s commitment to the project and improve the chance of funding. All that is necessary is that cost-sharing is enough to meet the agency’s minimum requirement for a high type proposal.
### Table 2.1

**Summary of Results**

<table>
<thead>
<tr>
<th>Case</th>
<th>Type of Equilibrium</th>
<th>Description of Equilibrium</th>
<th>Observations about equilibrium</th>
</tr>
</thead>
</table>
| 1    | Pooling if $C_A \leq C_L^{\text{MAX}}$ | $C^* = \min \{C_A, C_L^{\text{MAX}}\}$ | $\frac{\partial C^*}{\partial p} < 0$  
$\frac{\partial C^*}{\partial X_A} > 0$
$\frac{\partial C^*}{\partial G} > 0$
$\frac{\partial C^*}{\partial \Psi(H)} < 0$
$\frac{\partial C^*}{\partial \Psi(L)} < 0$ |
|      | Separating if $C_A > C_L^{\text{MAX}}$ | $C^* = C_{AH}^{\text{MIN}}$ | $\frac{\partial C^*}{\partial X_A} > 0$
$\frac{\partial C^*}{\partial G} > 0$
$\frac{\partial C^*}{\partial \Psi(H)} < 0$ |
| 2    | Separating           | $C^* = C_{AH}^{\text{MIN}}$ |                                |
| 3    | Pooling              | Neither type applies.       | There is no value of $C_H$ that satisfies both agency and university participation constraint. |
CHAPTER 3
EMPIRICAL TESTING OF THE MODEL

As described in the theoretical model developed in Chapter 2, the cost-sharing message sent by the university can provide information to the funding agency about the expected output that will come from a particular proposal. One prediction was that the cost-sharing level may be a function of the proposal’s preliminary assessment, p. In this instance, proposals with lower p rating will require a greater cost-sharing commitment from the university to gain funding, and those with excellent preliminary ratings will require much lower cost-sharing, ceteris paribus. I saw that in certain instances, as in Case 1 with $C_A > C_L^{\text{MAX}}$, this greater cost-sharing message could be an effective signal to the agency of true type. In other circumstances, as in Case 1 with $C_A \leq C_L^{\text{MAX}}$, I should observe the tradeoff between p and $C^*$, but the cost-sharing message will not result in a separating equilibrium. In Case 2, in which the agency’s threshold is relatively high, the cost-sharing message allows the agency to identify and fund only the high types. However, the relationship between p and $C^*$ is not expected.

This chapter seeks to test this basic theory of cost-sharing as a signal of type, as well as some of its predictions, such as the expected tradeoff between preliminary project assessment and the cost-sharing level.
3.1 The Empirical Framework

\[ CS = F(\text{TYPE}, \text{PRELIM}, \text{PUBLIC}, \text{EPSCOR}, \text{GRANT}, \text{UNIV}, \text{FIELD}, \text{YEAR}) \] (3.1a)

where:

CS = Amount of direct cost sharing that university commits towards the project. Usually, this will be expressed as a percentage of the project cost, but total cost-sharing will also be used occasionally to further explore variable relationships.

TYPE = Measured by the field normalized citations per publication from the grant and publications from the grant. This will serve as a proxy for the true type of the project. Recall that the true type of the project is unobservable by the agency at the time funding decision is made. Only ex post, by looking at the end result of the project, can true type be observed.

PRELIM = Preliminary assessment of the proposal’s type, represented by a vector of the following variables: NRC ranking of PI’s department, average of department’s equipment expenditures over five years, past track record of the PI (as measured by years of research experience and by their field normalized citations per publication or h index prior to the grant)

PUBLIC = Dummy variable equal to 1 if university is public and 0 if private. It is possible that there may be a connection between a university’s classification and their ability to cost-share. Additionally, it is possible that public universities may not be put under the same cost-sharing pressure that private universities face.

EPSCOR = Dummy variable equal to 1 if university is in a state that participates in the EPSCoR program; equal to 0 if in a non-EPSCoR state.

GRANT = Actual dollar value of grant awarded.

UNIV = Set of dummy variables for universities

FIELD = Set of dummy variables for fields

YEAR = Set of dummy variables for years
Two primary questions will be addressed during the testing of this model:

(1) What is the marginal effect of an increase in type on the level of cost-sharing (holding constant the agency’s preliminary assessment of type, characteristics of the university, and field of study)? In other words, does signaling occur? For example, does a type $T_H$ cost-share more or less than a type $T_L$ (where $T_H > T_L$)? Case 2 in the theoretical model of Chapter 2 suggested that among the high types, the cost-sharing offer will fall as their research output rises (recall $\partial C^*/\partial \Psi(H) < 0$).

(2) How does the agency’s preliminary assessment of the potential output of the project affect the level of cost-sharing? Ceteris paribus, does a university offer more cost-sharing for a proposal that has a lower preliminary assessment? (i.e. is there a tradeoff between proposal quality and cost-sharing)? Or, for high quality proposals, do universities feel less compelled to offer cost-sharing, thinking the proposal can stand on its own merit. These were the results predicted by the theoretical model in Chapter 2 under the Case 1 specification of the game.

3.2 Data & Methodology

The Office of Budget, Finance and Award Management of the National Science Foundation provided data on cost-sharing for continuing grants funded between 1993-2000 from their internal database of grants. It should be noted that even though the theoretical model in Chapter 2 was general and could be applied across funding agencies, the empirical testing is confined only to these NSF awards. Therefore, even though some general conclusions apply to the overall
funding of federal grants, I must be careful about extrapolating conclusions about the importance of specific variables to all agencies because of the potential for interagency differences that may exist.

Continuing grants are one of the primary funding mechanisms used by NSF. They are similar to another commonly-used competitive grant called a standard grant, in that the award is made to a specific principal investigator for a research project that has a definitive end date, usually 3 years. The primary difference is that the continuing grant is only awarded on a year-by-year basis, with the expectation that the grant will be renewed if the yearly goals of the project are being achieved. The standard grant is a multi-year award where no yearly review process is undertaken for funding to continue. Another important difference, and the reason why continuing grants were used for this dissertation, is that cost-sharing was much more likely to be an important element in the funding of continuing grants.

In creating the final data set, I only included continuing grants that would be expected to result in observable research output, i.e. publications. Other grants, such those aimed at establishing educational programs, were not included. For example, a common type of grant excluded because of this reason was the career grant, which frequently included elements of developing an educational program along with carrying out a research project. Because there is no feasible way to divide out the portion of the grant that was devoted to the research element, these types of continuing grants were excluded. Other awards were focused on stimulating research among students, such as the “research experience for undergraduates” awards. These also could not be
expected to produce the same type of research output as awards made to full-time researchers. I also excluded awards aimed solely at the purchase of equipment or the establishment of new facilities because they also could not be expected to directly produce publication output. In the final data set, I only used grants with positive cost-sharing levels. This decision was made because many of the grants with a zero value for cost-sharing may not have ever been considered for cost-sharing, perhaps because of some characteristic of the proposal related to unobservable factors outside the model. To correct for any potential selectivity bias that may result from this, I used the Heckman two-step procedure (Heckman, 1979). Using Excel’s random number generator, a random sample of 600 proposals was generated, including an equal number of proposals with and without cost-sharing. I ran a first stage probit model and used the results to calculate the inverse Mills ratio, which was subsequently incorporated into the regressions in this dissertation. The ratio, reported as \( \lambda \) in the results tables, was only significant at the .05 level in one of the 33 versions of the regression models, indicating that no significant selection bias was introduced. The complete results of this probit analysis are presented in section 3.4 below.

Table 3.1 lists the 17 scientific disciplines included in the final data set. These 17 disciplines fell into 5 NSF Directorates: Biological Sciences, Computer & Information Science, Engineering, Geosciences, and Mathematical & Physical Sciences. Finally, because of the need to ensure an adequate number of observations per university in running a university-fixed effects model, I dropped any university with less than 3 observations from the sample. The final data set used in the estimation procedure includes 1168 observations coming from 108 universities.
Table 3.1

NSF Divisions Included in Data Set

Astronomical sciences
Atmospheric sciences
Chemical, bioengineering, environmental and transport systems
Computing and communication foundations
Chemistry
Civil, mechanical and manufacturing innovation
Computer and network systems
Environmental biology
Materials research
Mathematical sciences
Earth sciences
Electrical, communications and cyber systems
Information and intelligent systems
Integrated organismal systems
Molecular and cellular biosciences
Ocean sciences
Physics

There were 2 notable limitations to the available data set that should be addressed. First, since cost-sharing data is only available on projects that were funded, the resulting data may be subject to a selection bias. It is important to note however that there is still a wide range of projects funded, as defined by a measure of research output such as citations that result from the grant or agency information such as citations prior to the grant. The mean and standard deviation for these variables are reported in Table 3.3. Also, because universities do not know their funding status when applying for the grant and making a cost-sharing offer, they will be choosing cost-sharing based on the factors observable to them. Thus, both primary questions described above can still be tested, but one should be careful about applying the conclusions broadly to all proposals submitted. Second, it is the policy of NSF to not release the scientific merit review
scores for the proposals to the public. However, because of the small variance in this data for funded proposals, there is reason to believe that the omitted variable bias is minimal. The average score among the 9,091 funded proposals in FY 2006 was a 4.2\(^1\). Also, among these funded proposals, approximately 78% of them received scores of 4 or 5. Less than 1% of funded proposals received scores of 1 or 2.

Data for the variable TYPE and for one of the measures of the researcher’s track record included in PRELIM resulted from a citation analysis that was performed. For the measurement of the researcher’s track record, total citations by the principal investigator prior to the grant award year, publications prior to the grant year and the h-index was collected using the “Science Citation Index” on the Web of Science (2008). The h-index, developed by Physicist Jorge Hirsch in 2005, attempts to capture both the quantity and quality of a researcher’s publication history. The index for a particular scientist would equal 20 if the scientist had 20 publications with at least 20 citations (Meho, 2007). The data on this measure was also collected using Web of Science.

There is a well-established literature describing the use of citation analysis as a method of measuring research impact. This is based on the fact that “scientists who have to say something important do publish their findings vigorously in the open, international journal literature” (Van Raan, 2003). Meho (2007) points out that citation analysis is being increasingly used in academia, from the use of “journal impact factors” in measuring journal quality to the use of

\(^1\) NSF merit review scores are reported on a scale of 1-5, with a score of 5 being “excellent” and a score of 1 being “fair to poor”. For more information on the merit review process, see NSF (2006).
citation counts by university tenure and promotion committees to measure research output. Meho also refers to the use of citation analysis by government funding agencies to evaluate a researcher’s body of work. Publications alone are a crude way of measuring research output because it does not capture the quality of the output, only the quantity. The use of citations from those publications seems to solve this problem, because citations will not only tend to rise with more publications, but will also rise as the quality of those publications rise (Diamond, 1993; Golden & Carstensen, 1992).

However, several potential pitfalls arise when performing a citation analysis that should be pointed out. First, there are alternative motives for citing a paper that are not a reflection of higher quality work. Numerous citations may reflect a positive impact of the publication on the field, but in some cases may result from a highly flawed work that is cited frequently in an attempt to correct the record (Kostoff, 1998). Kostoff also describes a problem known as the “Pied Piper Effect” in which a large number of citations may reflect an idea in a field that was once popular, but has been since proven incorrect. Finally, some of a paper’s citations may be self-citations or citations that originate from a network of researchers who tend to cite each other’s work in larger than usual numbers (Van Leeuwen et.al, 2001).

Another problem arises from factors that may influence the probability of being cited (Bornmann & Daniel, 2006). First, publications that have had more time to accumulate citations are more likely to have more citations. However, there is evidence that the average peak in citations occurs in the third or fourth year after publication in the life sciences (Moed et. al, 1995).
Therefore, papers arising from grants in the data set should have had adequate time to garner a majority of their citations. Bornmann & Daniel (2006) also point out that there are differences in citation practices across fields. The inclusion of field dummy variables will help alleviate these differences due to the field of study. Also, the use of the ratio CPP/FCSm will adjust the citations per publication for the differences in the mean number of citations per publication across fields (Van Leeuwen et al., 2001). Finally, Bornmann and Daniel note that papers cited in different languages may have unequal access to readers and thus citations may vary. Since the data being used includes only includes grant funding to U.S. researchers, this will not be an issue in this study.

Finally, the level of aggregation in a citation analysis can be a determining factor in the accuracy of the evaluation. A study of research impact at a university, department or research group level of analysis may more effectively smooth out some of the issues described above (Van Raan, 2003). In the data used in this dissertation, the publications are likely to be at the research group or individual level. However, there is support for performing the analysis at this level of aggregation in this case, as there are many publications resulting from the grant (8.4 = mean) and even more prior to the grant (66.8 = mean). So problems that may arise with individual publications, such as the negative intellectual heritage or the Pied Piper effect, will be smoothed out (Kostoff, 1998). Also, since the publications from the grant often represent the work of a research group over a number of years, the result is likely to yield a “strong indicator of scientific performance, and in particular of scientific quality” (Van Raan, 2003).
Other variables included in the PRELIM vector of variables include the principal investigator’s years of research experience prior to the award year, which is another indicator of track record, and average equipment expenditures by the researcher’s department over the 5 years prior to grant award year (in real 1996$). These equipment expenditures, derived from the online WebCASPAR database (NSF, 2008), not only represent complementary resources available to the researcher, but may also be a good reflection of department quality. The National Research Council’s 1995 report, Research-Doctorate Programs in the United States, which is a survey of the scholarly quality of faculty, gives another measure of department quality. The survey instrument was sent to faculty working in the field and asked the rater to assign a 0-5 score for the scholarly quality of the faculty in the department for over 50 departments. The goal was to attain at least 100 ratings of each program. The survey came under some criticism because of a “halo effect” that led to programs in prestigious universities being given higher ratings than warranted and a “star effect” that led to the over-rating of programs with a notable researcher. It was also criticized because rater’s views of departments may under-estimate upcoming departments and give too much credit to departments that previously had a high reputational ranking (NRC, 2003). In other words, ratings tend to be sticky, or as stated on page 37 of the 2003 NRC Assessment study, “In fact, reputational ratings change very slowly over time…” Interestingly, this criticism of the report actually lends support to the use of the fixed 1995 ranking as an approximation of reputation over the course of the whole data set, which ranges between 1993 and 2000. Despite the above criticisms, the scholarly ranking of departments was the most widely used portion of the NRC report. For the science and engineering fields, the measure also tended to be significantly correlated with other quantitative measures of quality,
such as publications per faculty or citations per faculty (NRC, 1995). This not only supports the usefulness of the measure as a measure of department quality, but also provides another example of the use of citation analysis in academia. In the newest version of the NRC report due to be released in September 2008, these other quantitative measures will play a larger role in creating the reputational rankings.

To account for unobservable heterogeneity across universities or fields that may impact the level of cost-sharing, I used a set of dummy variables to create a fixed effects model. For example, the size of the university’s research budget will affect the university’s threshold and therefore the cost-sharing offer. There may also be underlying political factors that could affect the cost-sharing offer and these effects will be picked up with the university dummies. From looking at the growing amount of earmarked research dollars going to universities\(^\text{13}\), it is clear that politics play a role in the allocation of research funds. These unobservable political factors may also be at play in the awarding of competitive grants as well.

Other characteristics of universities that are measurable and may be of interest are represented by separate dummy variables. I included the dummy variables PUBLIC, which notes the public/private status of the university, and EPSCOR, which is a program to stimulate research in lagging states, to test whether these specific factors affected cost-sharing.

Finally, I added year dummy variables in order to control for heterogeneity in cost-sharing that

---

\(^{13}\) During the period 1980-2003, academic earmarking rose by 5,900\% in real dollar terms. (Figueiredo &
may have occurred due to factors related to time. For example, the agency’s threshold level may be affected by the year in which the grant was awarded. Table 3.2 suggests that this may have been occurring over the 1993-2000 period. Over the course of this time period, the number of proposals received by NSF fell, from 30,003 to 29,407\textsuperscript{14}. In addition, the portion of NSF’s budget devoted to research funding rose in constant dollars during each year\textsuperscript{15}. As a result, for each year, the ratio of the total number of proposals considered by NSF divided by NSF’s annual budget became smaller. On the surface, this seems to suggest that since there were less proposals competing for a larger pool of funds, and the agency’s threshold value would be smaller. However, at the same time, the average award was rising. So it is unclear from this measure if the funding environment was becoming looser at all. Thus, I report the results of using “proposals per dollar” as a measure of a changing agency threshold and the alternative, a year fixed effects approach.

\begin{table}[h]
\centering
\begin{tabular}{|l|l|l|l|l|l|l|l|}
\hline
\hline
11.17 & 10.91 & 10.69 & 10.52 & 10.22 & 9.18 & 8.54 & 8.51 \\
\hline
\end{tabular}
\caption{Proposals Submitted Divided by NSF Research Budget (in millions of constant dollars)}
\end{table}

Table 3.3 below describes the distribution of the variables used in the empirical model.

\textsuperscript{14}See (NSF, 2000).

\textsuperscript{15}Silverman, 2007)
Table 3.3

Descriptive Statistics, Variables of Interest

<table>
<thead>
<tr>
<th>Variables of Interest</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost-sharing ($)</td>
<td>$49,368</td>
<td>$143,344</td>
</tr>
<tr>
<td>Total award</td>
<td>$492,627</td>
<td>$1,338,235</td>
</tr>
<tr>
<td>Equipment R&amp;D of Dept., 5 yr. ave.</td>
<td>$774,050</td>
<td>$1,168,544</td>
</tr>
<tr>
<td>Research Experience (in years)</td>
<td>17.02</td>
<td>9.82</td>
</tr>
<tr>
<td>NRC Dept. Score</td>
<td>3.218</td>
<td>.765</td>
</tr>
<tr>
<td>Publications before grant</td>
<td>65.98</td>
<td>85.09</td>
</tr>
<tr>
<td>Citations before grant</td>
<td>2,059.64</td>
<td>3,211.07</td>
</tr>
<tr>
<td>Citations per publication (CCP) before grant</td>
<td>29.23</td>
<td>24.84</td>
</tr>
<tr>
<td>Field Normalized CCP (CCP/FCSm) before grant</td>
<td>5.24</td>
<td>5.31</td>
</tr>
<tr>
<td>h index for researcher</td>
<td>19.18</td>
<td>14.41</td>
</tr>
<tr>
<td>Publications from grant</td>
<td>8.42</td>
<td>9.25</td>
</tr>
<tr>
<td>Citations from grant</td>
<td>165.81</td>
<td>356.99</td>
</tr>
<tr>
<td>Citations per publication (CCP) from grant</td>
<td>17.99</td>
<td>27.53</td>
</tr>
<tr>
<td>Field Normalized CCP (CCP/FCSm) from grant</td>
<td>4.01</td>
<td>7.64</td>
</tr>
</tbody>
</table>

3.3 An Analysis of Variance

Table 3.4 below describes the data set in terms of different university classification schemes. For each, the result of an F test to determine the significance of differences in means is reported. There is no significant difference for public and private universities. Most interesting, I find that proposals in the data set originating from universities in the Experimental Program to Stimulate Competitive Research actually cost-shared at a higher percentage than those from non-EPSCoR states. The theoretical model would explain this result in terms of the tradeoff between proposal quality and cost-sharing. Researchers at these institutions are more likely to have shorter track records and come from departments with lower reputations and less equipment than researchers.

15 Data obtained from the National Science Foundation’s online Budget Internet Information System.
coming from the population as a whole. The model predicts that proposals such as these, with low preliminary assessment values, offered more cost-sharing to gain the funding they received.

Finally, Table 3.4 shows that a university’s Carnegie Classification is a statistically significant correlate of cost-sharing percentages. R1 universities are more likely to have well-established research programs than universities from the other classes. The same can be said about R2 universities compared to D1 and D2 institutions. Thus, just as with non-EPSCoR universities, researchers at higher classified institutions are more likely to have better track records, greater departmental reputations, and superior facilities. All of these factors could improve their preliminary project assessment and decrease the need for cost-sharing.
Table 3.4

Cost-sharing Percentages by University Category

<table>
<thead>
<tr>
<th>Number of Observations</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost-sharing of projects (%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All Projects</td>
<td>1168</td>
<td>9.21</td>
</tr>
<tr>
<td>Public universities only</td>
<td>903</td>
<td>9.37</td>
</tr>
<tr>
<td>Private universities only</td>
<td>265</td>
<td>8.67</td>
</tr>
<tr>
<td>F = 1.019 (p = .313)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EPSCoR states only</td>
<td>97</td>
<td>12.22</td>
</tr>
<tr>
<td>Non-EPSCoR states only</td>
<td>1071</td>
<td>8.94</td>
</tr>
<tr>
<td>F = 9.737 (p = .002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R1 Carnegie Classification</td>
<td>949</td>
<td>8.63</td>
</tr>
<tr>
<td>R2 Carnegie Classification</td>
<td>149</td>
<td>10.49</td>
</tr>
<tr>
<td>D1 Carnegie Classification</td>
<td>37</td>
<td>12.61</td>
</tr>
<tr>
<td>D2 Carnegie Classification</td>
<td>33</td>
<td>16.44</td>
</tr>
<tr>
<td>F = 9.326 (p = .000)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Tables 3.5 and 3.6 explore some of the other relationships in the data. In 3.5, we see that there is a strongly significant relationship between the NSF division from which the award was granted and the cost-sharing percentage. This might be explained by differences in the types of projects being funded, e.g. engineering projects may involve larger requests for long-lived equipment, which traditionally involve greater cost-sharing components. Alternatively, there may be different budget constraints place on program managers within different divisions. If a particular field is considered a current priority, program managers may be free to fund projects at lower
Table 3.5

Cost-sharing Percentage by NSF Division

<table>
<thead>
<tr>
<th>NSF Divisions by Directorate</th>
<th>Number of Observations</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biological Sciences</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Environmental Biology</td>
<td>53</td>
<td>9.61</td>
<td>10.20</td>
</tr>
<tr>
<td>Integrated Organismal Systems</td>
<td>40</td>
<td>13.11</td>
<td>11.55</td>
</tr>
<tr>
<td>Molecular and Cellular Biosciences</td>
<td>68</td>
<td>7.53</td>
<td>8.14</td>
</tr>
<tr>
<td>Computer and Information Science</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Computing and Communications Foundations</td>
<td>92</td>
<td>9.11</td>
<td>10.87</td>
</tr>
<tr>
<td>Computer and Network Systems</td>
<td>6</td>
<td>10.85</td>
<td>14.63</td>
</tr>
<tr>
<td>Information and Intelligence Systems</td>
<td>113</td>
<td>8.25</td>
<td>8.08</td>
</tr>
<tr>
<td>Engineering</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chemical, Bioengineering, Environmental and Transport Systems</td>
<td>110</td>
<td>9.43</td>
<td>10.09</td>
</tr>
<tr>
<td>Civil, Mechanical and Manufacturing Innovation</td>
<td>85</td>
<td>16.44</td>
<td>14.89</td>
</tr>
<tr>
<td>Electrical Communications and Cyber Systems</td>
<td>43</td>
<td>14.69</td>
<td>12.41</td>
</tr>
<tr>
<td>Geosciences</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Atmospheric Sciences</td>
<td>105</td>
<td>7.12</td>
<td>8.23</td>
</tr>
<tr>
<td>Earth Sciences</td>
<td>29</td>
<td>5.85</td>
<td>5.44</td>
</tr>
<tr>
<td>Oceanography</td>
<td>20</td>
<td>4.36</td>
<td>3.24</td>
</tr>
<tr>
<td>Mathematical and Physical Sciences</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Astronomical Sciences</td>
<td>5</td>
<td>3.93</td>
<td>1.35</td>
</tr>
<tr>
<td>Chemistry</td>
<td>141</td>
<td>8.59</td>
<td>6.62</td>
</tr>
<tr>
<td>Materials Research</td>
<td>125</td>
<td>7.50</td>
<td>6.24</td>
</tr>
<tr>
<td>Mathematical Sciences</td>
<td>44</td>
<td>5.93</td>
<td>6.54</td>
</tr>
<tr>
<td>Physics</td>
<td>89</td>
<td>9.89</td>
<td>13.18</td>
</tr>
</tbody>
</table>

F = 6.539 (p = 0.000)
cost-sharing levels, i.e. the threshold level may be lower for that division. Table 3.6 examines how cost-sharing percentages have changed over time. An F test shows that we cannot conclude a statistically significant difference between means.

Table 3.6

Cost-sharing Percentage by Grant Year

<table>
<thead>
<tr>
<th>Grant Year</th>
<th>Number of Observations</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>1993</td>
<td>21</td>
<td>6.33</td>
<td>6.21</td>
</tr>
<tr>
<td>1994</td>
<td>118</td>
<td>9.18</td>
<td>10.47</td>
</tr>
<tr>
<td>1995</td>
<td>211</td>
<td>8.75</td>
<td>10.50</td>
</tr>
<tr>
<td>1996</td>
<td>169</td>
<td>8.21</td>
<td>10.03</td>
</tr>
<tr>
<td>1997</td>
<td>179</td>
<td>9.04</td>
<td>9.64</td>
</tr>
<tr>
<td>1998</td>
<td>135</td>
<td>9.04</td>
<td>8.87</td>
</tr>
<tr>
<td>1999</td>
<td>161</td>
<td>10.45</td>
<td>10.23</td>
</tr>
<tr>
<td>2000</td>
<td>174</td>
<td>10.29</td>
<td>9.98</td>
</tr>
</tbody>
</table>

F = 1.223 (p = 0.287)

3.4 Results and Discussion

Prior to running the estimation procedure, I examined the data for multicollinearity and found a strong multicollinearity problem between the dummy variable for EPSCoR status and the university dummies. EPSCoR was dropped from the full model. Its relationship will be explored in another specification of the model. There was also a significant correlation between publications before grant and research experience. Since there are other bibliometric measures of
research impact that are superior to number of publications, such as CPP/FCSm, number of publications before grant were not used in the final testing. Finally, using this measure CPP/FCSm, created a multicollinearity problem with the field dummy variables. This problem is discussed below. There were no other significant multicollinearity issues between the explanatory variables.

Table 3.7 below reports the results of the probit analysis. Although the overall probit model was significant at the .0000 level, only total award was significant among the seven variables of interest. However, the magnitude of the coefficient for total award reveals that there was no measurable impact on whether the grant involved cost-sharing. Conducting a likelihood ratio test on each of the fixed effects components revealed that university, field, and year were each significant with p values of .0009, .0000, and .0000 levels, respectively. These results buttress the results of the full model described in the tables that follow, that cost-sharing seems to be determined by the threshold of the university and by the threshold of the agency, which may vary by field or year.
Table 3.7

1st Stage Probit Model

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CPP/FCSm from grant (“TYPE”)</strong></td>
<td>0.019</td>
<td>(0.016)</td>
</tr>
<tr>
<td><strong>Publications from grant (“TYPE”)</strong></td>
<td>-0.002</td>
<td>(0.009)</td>
</tr>
<tr>
<td><strong>Equipment</strong></td>
<td>0.000</td>
<td>(0.000)</td>
</tr>
<tr>
<td><strong>Research Experience</strong></td>
<td>0.007</td>
<td>(0.008)</td>
</tr>
<tr>
<td><strong>CPP/FCSm before grant</strong></td>
<td>-0.013</td>
<td>(0.014)</td>
</tr>
<tr>
<td><strong>NRC Dept. Rating</strong></td>
<td>0.013</td>
<td>(0.196)</td>
</tr>
<tr>
<td><strong>Total Award</strong></td>
<td>0.001 **</td>
<td>(0.000)</td>
</tr>
</tbody>
</table>

**Fixed Effects**

---University Yes
---Field Yes
---Year Yes

**Chi-Square value** 386.508 (p = 0.000)

**N** 600

**Pseudo R-squared** 0.475

Note: * indicates significance at the .10 level and ** indicates significance at the .05 level.

Results of the full model with cost-sharing percentage as the dependent variable and with university, field and time fixed effects are reported in Table 3.8, column 1. I conducted a pooling test to check for the significance of the fixed effects components. University and field were each found to be significant at the .001 level using cost-share % for the dependent variable, while year was only significant at the .1 level. For the total cost-share $ model, only year was significant, and at the .05 level. This confirms that there is heterogeneity due to university and field differences for cost-share %, but only a marginal relationship with time apparent. It makes
intuitive sense that there are differences across time for total cost-share dollars, because total award size was increasing over this time period. This fixed effects approach eliminates potential omitted variable bias that would exist in a standard cross-sectional model if the variables causing these differences are unobservable. For the university, these unobservable factors relate to the university’s threshold level that was described in the model in Chapter 2 or the unobservable political factors described earlier this chapter. The agency’s threshold could be related to time-dependent factors, as agency budgets could tighten or loosen over time, or the field of study, as funding certain fields could be a greater national priority. So the significance of the field fixed effects in column 1 says that cost-sharing practices vary by field. Compared to the omitted category, physics, which was approximately in the middle of the ranking of fields by mean cost-sharing %, there were two examples of highly significant individual fields. These were Civil/Mechanical/Manufacturing Engineering with a coefficient of +8.42 (p=.0001) and Electrical Engineering with a coefficient of +5.93 (p=.0131). We will explore more of these interagency differences later in this chapter. Table 3.2, which followed the ratio of proposals to NSF research budget over the data period, lent support to the idea that this threshold may be time dependent.
Table 3.8

Fixed Effects Cost-Sharing Full Models

<table>
<thead>
<tr>
<th></th>
<th>(1) Full Model Cost-Share %</th>
<th>(2) Full Model Cost-Share $ ('000s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>------------------------------------</td>
<td>-----------------------------</td>
<td>-------------------------------------</td>
</tr>
<tr>
<td>CPP/FCSm from grant (“TYPE”)</td>
<td>-0.0004 (0.0339)</td>
<td>-0.0848 (0.3722)</td>
</tr>
<tr>
<td>Publications from grant (“TYPE”)</td>
<td>-0.0171 (0.0365)</td>
<td>0.3290 (0.8934)</td>
</tr>
<tr>
<td>Equipment $ ('000s)</td>
<td>-0.0002 (0.0004)</td>
<td>-0.0040 (0.0068)</td>
</tr>
<tr>
<td>Research Experience (years)</td>
<td>0.0061 (0.353)</td>
<td>0.1342 (0.4033)</td>
</tr>
<tr>
<td>CPP/FCSm before grant</td>
<td>0.0365 (0.0811)</td>
<td>0.2827 (0.4978)</td>
</tr>
<tr>
<td>NRC Dept. Rating</td>
<td>0.9496 * (0.6031)</td>
<td>7.9503 (6.3568)</td>
</tr>
<tr>
<td>Total Award ('000s)</td>
<td>-0.0002 (0.0002)</td>
<td>0.0688 * (0.0401)</td>
</tr>
<tr>
<td>F-value (variables of interest)</td>
<td>0.5918 (p = 0.7630)</td>
<td>2.4170 (p = 0.0186)</td>
</tr>
<tr>
<td>$</td>
<td>0.8246 (0.5137)</td>
<td>6.5163 (4.3839)</td>
</tr>
</tbody>
</table>

Fixed Effects
---University Yes Yes
---Field Yes Yes
---Year Yes Yes
F-value (full model) 13.9467 (p = 0.0000) 8.5033 (p = 0.0000)
N 1168 1168
R-squared 0.6141 0.5444

Note: * indicates significance at the .10 level and ** indicates significance at the .05 level. Heteroskedasticity-consistent standard errors are shown in parentheses.

With regard to the overall goodness of fit of the model described in column 1, the highly significant F value, the strong R², the strong significance of the university and field fixed effects, and the marginal significance of the year fixed effects suggest that the model is well specified.

Also, the insignificance of the inverse Mills ratio ($\lambda$) suggests that the inclusion of only those
proposals with positive cost-sharing did not introduce any selectivity bias. However, the lack of significance from some key variables suggests that further alternative specifications are warranted in order to examine those variables in more detail. In regard to the 2 key questions identified earlier in this chapter, there is some information provided in column 1. One of these primary questions of interest relates to the prediction made in Case 1 of the theoretical model. That is, do proposals with higher p, i.e. those with more favorable preliminary factors, not require as much cost-sharing as those with a lower preliminary agency assessment. The empirical model included 4 variables that were designed to test this prediction made by the theory. Of those 4 variables, NRC department rating was found to be marginally significant (at the .10 level of significance), but the sign of the coefficient was initially somewhat troubling. Instead of having an inverse relationship with cost-sharing as predicted, the result suggests a positive relationship between the preliminary assessment of the project and cost-sharing level. This seemingly contradictory result could be explained if NRC department rating is picking up the heterogeneous characteristics of the department, such as the ability of the department to cost-share. When cost-sharing originates from the department level, rather than the university level, it would be the research budget of the department that would determine the ability to cost-share. Thus, the relevant threshold would not originate from the university, but from the department. With lower thresholds, the department has greater freedom to cost-share at higher levels if needed to attain the grant. Thus, NRC department seems to be serving as a proxy for this departmental influence. We see that an increase in the NRC rating by 1 point would be expected to approximately a 1% increase in cost-sharing. With regard to the other key question, do higher types cost-share less than types with lower research output, there is no significant relationship
between either measures of type (publications from grant or CCP/FCSm from grant) to address the question here.

Column 2 of Table 3.8 repeats the analysis of the model reported in column 1, except that the dependent variable is changed to the level of cost-sharing in dollars. The variable NRC Department is no longer significant in this formulation, but one new variable, total grant award, becomes marginally significant (at a .1 level of significance). Specifically, it predicts that for every $1,000 increase in total award, there is approximately a $69 increase in cost-sharing. The positive sign on the estimated coefficient indicates that larger awards are associated with larger levels of cost-sharing. This result, although intuitive, is significant in terms of providing additional support to the theoretical model, which predicted this relationship. The insignificant result for total grant award that was found in column 1 does not contradict this expected relationship. That result simply did not establish a relationship between the grant size and percent cost-sharing.
### Table 3.9

**Fixed Effects Cost-Sharing Reduced Models**

<table>
<thead>
<tr>
<th></th>
<th>(3) Reduced Model No Univ. Cost-Share %</th>
<th>(4) Reduced Model No Univ. Cost-Share $ (‘000s)</th>
<th>(5) Reduced Model No NSF Field Cost-Share%</th>
<th>(6) Reduced Model No NSF Field Cost-Share $ (‘000s)</th>
<th>(7) Reduced Model No Year Cost-Share%</th>
<th>(8) Reduced Model No Year Cost-Share $ (‘000s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPP/FCSm from grant (“TYPE”)</td>
<td>-0.0187 (0.0320)</td>
<td>-0.2378 (0.2341)</td>
<td>0.0058 (0.0343)</td>
<td>-0.0273 (0.3843)</td>
<td>-0.0106 (0.3863)</td>
<td>-0.3271 (0.3863)</td>
</tr>
<tr>
<td>Publications from grant (“TYPE”)</td>
<td>0.0378 (0.0341)</td>
<td>0.5674 (0.7841)</td>
<td>-0.0081 (0.0344)</td>
<td>0.4627 (0.8949)</td>
<td>-0.0131 (0.0359)</td>
<td>0.4537 (0.9042)</td>
</tr>
<tr>
<td>Equipment $ (000’s)</td>
<td>-0.0004 (0.0003)</td>
<td>-0.0056 (0.0054)</td>
<td>-0.0002 (0.0003)</td>
<td>-0.0016 (0.0059)</td>
<td>-0.0001 (0.0004)</td>
<td>-0.0024 (0.0069)</td>
</tr>
<tr>
<td>Research Experience (years)</td>
<td>0.0858 ** (0.0362)</td>
<td>0.3829 (0.4165)</td>
<td>-0.0564 (0.0348)</td>
<td>-0.1772 (0.3879)</td>
<td>0.0098 (0.0358)</td>
<td>0.1821 (0.4046)</td>
</tr>
<tr>
<td>CPP/FCSm before grant</td>
<td>0.0143 (0.0840)</td>
<td>0.1872 (0.5090)</td>
<td>0.0163 (0.0752)</td>
<td>0.1872 (0.4385)</td>
<td>0.0298 (0.0805)</td>
<td>0.1349 (0.4940)</td>
</tr>
<tr>
<td>NRC Dept. Rating</td>
<td>0.5068 (0.4111)</td>
<td>2.5635 (5.298)</td>
<td>0.9716 * (0.5629)</td>
<td>6.8474 (5.9345)</td>
<td>0.7279 (0.5739)</td>
<td>5.0352 (5.6173)</td>
</tr>
<tr>
<td>Total Award $ (‘000s)</td>
<td>-0.0001 (0.0002)</td>
<td>0.0696 * (0.0396)</td>
<td>-0.0002 (0.0002)</td>
<td>0.0687 * (0.0388)</td>
<td>-0.0002 (0.0002)</td>
<td>0.0688 * (0.0402)</td>
</tr>
<tr>
<td>F-value (variables of interest)</td>
<td>1.6788 (p = 0.1103)</td>
<td>4.1761 (p = 0.0001)</td>
<td>0.9040 (p = 0.5025)</td>
<td>3.1222 (p = 0.0029)</td>
<td>0.4890 (p = 0.8430)</td>
<td>2.9013 (p = 0.0052)</td>
</tr>
<tr>
<td>λ</td>
<td>-0.1174 (0.1971)</td>
<td>-1.6763 (1.3792)</td>
<td>0.2526 (0.4247)</td>
<td>2.4868 (3.5839)</td>
<td>0.7862 (0.4903)</td>
<td>6.1596 (4.1857)</td>
</tr>
</tbody>
</table>

**Fixed Effects**

---University  No  No  Yes  Yes  Yes  Yes  Yes
---Field       Yes  Yes  No  No  Yes  Yes  Yes
---Year        Yes  Yes  Yes  No  No  No  No

<table>
<thead>
<tr>
<th>F-value (full model)</th>
<th>38.2686 (p = 0.0000)</th>
<th>21.0712 (p = 0.0000)</th>
<th>14.1233 (p = 0.0000)</th>
<th>9.0794 (p = 0.0000)</th>
<th>13.5018 (p = 0.0000)</th>
<th>8.4093 (p = 0.0000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>1168</td>
<td>1168</td>
<td>1168</td>
<td>1168</td>
<td>1168</td>
<td>1168</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.4802</td>
<td>0.4957</td>
<td>0.5857</td>
<td>0.5381</td>
<td>0.6100</td>
<td>0.5380</td>
</tr>
</tbody>
</table>

Note: * indicates significance at the .10 level and ** indicates significance at the .05 level. Heteroskedasticity-consistent standard errors are shown in parentheses.
Table 3.9 listed shown above lists the results of 6 reduced forms of the model that I ran in attempt to flesh out what effects the 3 types of fixed effects variables were having on the model. When university is removed in column 3, NRC department score completely loses its significance, but research experience becomes strongly significant and has a positive, although small impact on cost-sharing %. The coefficient shows that cost-sharing % will rise by .09% for every additional year in experience. This was one of the measures of the agency’s preliminary assessment of the project. We expected that these preliminary assessment variables should be negatively related to the level of cost-sharing, and although the positive sign on the estimated coefficient for research experience seems to refute this prediction, the actual impact is so small that it is not of significant concern, but does prompt me to explore the research experience variable further. Note that in this version of the model, R² suffers some from the exclusion of the university dummies, suggesting this reduced form is not as good at explaining cost-sharing. However, it does imply that there is some relationship between experience and university dummies. For column 4, which represents the results of the no university dummy specification for total cost-sharing $, there is no change in variable significance from column 2. However, again R² suffers, lending additional support to the inclusion of the university dummies in the true model. I will return to Columns 5-8 after an exploration of the research experience variable and also further exploration of the university effects.

Table 3.10, displayed below, contains the results of the analysis when the data is stratified by research experience. Because of the restricted sample, Carnegie Classification and directorate fixed effects were used in place of university and field fixed effects. A couple of interesting
results are of note here. For younger researchers, defined as having less than 10 years of research experience, NRC department and public/private dummy were both highly significant. This implies that a department with greater prestige has more resources to devote towards cost-sharing, allowing them to support younger researchers who may have a low preliminary assessment because of this short track record. For veteran researchers, defined as having at least 25 years of research experience, research experience is highly significant and has a positive impact on cost-sharing. Specifically, for each year increase in experience, cost-sharing % rises by .18%. This might be explained by these researchers having better access to institutional support, thus impacting the ability to cost-share. In other words, universities may be more willing to support established researchers than younger or untenured faculty. Because of the positive relationship between research experience and cost-sharing, even among the veteran researcher group, even greater experience meant even greater support from the department. This research experience variable was originally included because it was thought that it would be a significant factor used by the agency to determine the preliminary assessment. We predicted that the coefficient on research experience would be negative. However, it appears that the more important impact of research experience may be on the threshold of the university. But since this is an individual researcher level variable, this means that it may be better to describe the university’s threshold level as varying by researcher, as well as department (as shown by the NRC department variable being highly significant for young researchers or being marginally significant for the full model) or university (as shown by the university or Carnegie
Table 3.10

Fixed Effects Cost-Sharing by Research Experience

<table>
<thead>
<tr>
<th></th>
<th>(9) Research Experience ≤ 10 yrs. Cost-Share %</th>
<th>(10) Research Experience ≥ 25 yrs. Cost-Share %</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPP/FCSm from grant (&quot;TYPE&quot;)</td>
<td>-0.0560 (0.0456)</td>
<td>0.0676 (0.1994)</td>
</tr>
<tr>
<td>Publications from grant (&quot;TYPE&quot;)</td>
<td>0.0606 (0.0628)</td>
<td>-0.1111 (0.0767)</td>
</tr>
<tr>
<td>Equipment$ ('000s)</td>
<td>-0.0001 (0.0007)</td>
<td>-0.0001 (0.0006)</td>
</tr>
<tr>
<td>Research Experience (years)</td>
<td>0.1465 (0.2554)</td>
<td>0.1830 ** (0.0945)</td>
</tr>
<tr>
<td>CPP/FCSm before grant</td>
<td>0.0015 (0.1353)</td>
<td>0.0772 (0.3269)</td>
</tr>
<tr>
<td>NRC Dept. Rating</td>
<td>2.1172 ** (1.0592)</td>
<td>-0.1561 (1.3414)</td>
</tr>
<tr>
<td>Total Award ('000s)</td>
<td>-0.0012 (0.0011)</td>
<td>-0.0001 (0.0002)</td>
</tr>
<tr>
<td>F-value (variables of interest)</td>
<td>1.2994 (p = 0.2499)</td>
<td>1.0914 (p = 0.3693)</td>
</tr>
<tr>
<td>Public DV (=1 if public university)</td>
<td>5.3861 ** (1.8279)</td>
<td>2.5267 (1.5460)</td>
</tr>
<tr>
<td>EPSCoR DV (=1 if EPSCoR)</td>
<td>3.8057 (3.4963)</td>
<td>1.7192 (3.2320)</td>
</tr>
<tr>
<td>λ</td>
<td>-0.0098 (0.3431)</td>
<td>-0.6111 (0.4369)</td>
</tr>
</tbody>
</table>

Fixed Effects
---Carnegie Class Yes Yes
---Directorate Yes Yes
---Year Yes Yes
F-value (full model) 15.3882 (p = 0.0000) 9.0744 (p = 0.0000)
N 346 262
R-squared 0.5433 0.4652

Note: * indicates significance at the .10 level and ** indicates significance at the .05 level. Heteroskedasticity-consistent standard errors are shown in parentheses. The F value for the Chow test was 1.3691 with a p value of 0.0502.
Classification fixed effects being significant). To determine if there is a significant difference between the two models presented in Table 3.10, I ran a Chow test. The resulting F value of 1.3691 was significant at the .0502 level of significance, indicating that there is a strong reason to believe that the coefficients resulting from these two subsamples are significantly different from each other. This supports discussing the subsample results separately. For the remainder of the dissertation, this Chow test was repeated in each case that the data set was divided in subsamples, and the results are reported in the notes to the tables that follow, when applicable. In each case, the test yielded a significant result.

When the NSF field dummies are removed, similar results are attained as that in the full model, see columns 5 & 6 in Table 3.9. NRC department is again marginally significant and has almost the identical impact on cost-sharing. Also, total award is still marginally significant and almost identical in impact. In columns 7 & 8, the removal of the year dummies completely removes the effect of NRC on cost-share %, but the almost identical relationship between total award and total cost-sharing remains.

I will refer to Table 3.11, column 11, to examine the effect of using an alternative for university fixed effects. Using Carnegie Classification as a substitute yields a significant pooling test at the .001 level of significance and the inclusion of the EPSCoR dummy yields a marginally significant result. This lends support to the use of these substitutes, especially Carnegie Classification, in place of university when needed to run a model with less observations and missing values for universities, as was the case in the models in columns 9 and 10. Notice that
the Public/Private dummy is highly significant in this model. This shows that, controlling for Carnegie Classification, EPSCoR status, and the other variables of interest, public universities will cost-share 1.98% greater than private universities.

Column 12 shows the results of the full model with replacement of field with directorate. Here, a pooling test on directorate shows a significant result at the .001 level of significance. This lends support to the use of directorate as a substitute for field when necessary, as in Table 3.10.
# Table 3.11
Fixed Effects Cost-Sharing Models with Replacement

<table>
<thead>
<tr>
<th></th>
<th>(11) Reduced Model Includes CC &amp; EPSCoR Status Cost-Share%</th>
<th>(12) Reduced Model Includes NSF Directorate Cost-Share%</th>
<th>(13) Reduced Model Includes NSF Budget Cost-Share%</th>
<th>(14) Reduced Model Includes Proposals/NSF Budget Cost-Share%</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPP/FCSm from grant (“TYPE”)</td>
<td>-0.0101 (0.0327)</td>
<td>-0.0031 (0.0340)</td>
<td>0.0024 (0.0339)</td>
<td>-0.0065 (0.0327)</td>
</tr>
<tr>
<td>Publications from grant (“TYPE”)</td>
<td>0.0088 (0.0352)</td>
<td>-0.0038 (0.0353)</td>
<td>-0.0187 (0.0361)</td>
<td>-0.0160 (0.0361)</td>
</tr>
<tr>
<td>Equipment $ (000’s)</td>
<td>-0.0002 (0.0003)</td>
<td>-0.0002 (0.0003)</td>
<td>-0.0001 (0.0004)</td>
<td>-0.0002 (0.0004)</td>
</tr>
<tr>
<td>Research Experience</td>
<td>0.0404 (0.0338)</td>
<td>-0.0133 (0.0349)</td>
<td>-0.0028 (0.0353)</td>
<td>0.0104 (0.0357)</td>
</tr>
<tr>
<td>CPP/FCSm before grant</td>
<td>0.0142 (0.0811)</td>
<td>-0.0071 (0.0730)</td>
<td>0.0248 (0.0837)</td>
<td>0.0388 (0.0805)</td>
</tr>
<tr>
<td>NRC Dept. Rating</td>
<td>0.3140 (0.5147)</td>
<td>0.9363 * (0.5490)</td>
<td>-0.0519 (0.6453)</td>
<td>1.1996 * (0.6934)</td>
</tr>
<tr>
<td>Total Award</td>
<td>-0.0001 (0.0002)</td>
<td>-0.0002 (0.0002)</td>
<td>-0.0003 (0.0002)</td>
<td>-0.0002 (0.0002)</td>
</tr>
<tr>
<td>F-value (variables of interest)</td>
<td>0.4049 (p = 0.8997)</td>
<td>0.5652 (p = 0.7845)</td>
<td>0.3049 (p = 0.9518)</td>
<td>0.6922</td>
</tr>
<tr>
<td>Public DV (=1 if public university)</td>
<td>1.9764 ** (0.7569)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EPSCoR DV (=1 if EPSCoR)</td>
<td>2.7357 * (1.4494)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NSF Budget</td>
<td></td>
<td></td>
<td>0.0029 ** (0.0009)</td>
<td>-0.4518 * (0.2576)</td>
</tr>
<tr>
<td>Proposals/NSF Budget</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \lambda )</td>
<td>-0.1181 (0.1978)</td>
<td>0.6275 (0.4639)</td>
<td>0.7671 (0.4707)</td>
<td>0.7739 (0.4893)</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>---University</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>---CC</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>---Field</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>---Directorate</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>---Year</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>F-value (full model)</td>
<td>34.4620 (p = 0.0000)</td>
<td>15.2367 (p = 0.0000)</td>
<td>14.2489 (p = 0.0000)</td>
<td>13.8516 (p = 0.0000)</td>
</tr>
<tr>
<td>N</td>
<td>1168</td>
<td>1168</td>
<td>1168</td>
<td>1168</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.4991</td>
<td>0.5995</td>
<td>0.6138</td>
<td>0.6112</td>
</tr>
</tbody>
</table>

Note: * indicates significance at the .10 level and ** indicates significance at the .05 level. Heteroskedasticity-consistent standard errors are shown in parentheses.
We will discuss columns 13 and 14 of this table later in this chapter when examining the year fixed effects in more detail.

I will finish the discussion of the university heterogeneity by looking at the model divided into subsets by the Carnegie Classification, see Table 3.12. There are two interesting results here that I will focus attention on. First, note that for the more research-intensive universities, NRC department is highly significant and has a positive relationship with cost-sharing. For R1, an increase in ranking by 1 leads to a 1.49% increase in cost-sharing. For R2, the number is even larger, at 2.48%. This effect is completely absent in the D1 and D2 subsets. This is further evidence that there is a direct NRC department and cost-sharing relationship. However, Table 3.11 elaborates on this relationship by suggesting that it does not hold for universities in lower Carnegie Classification. What we see is that this effect is concentrated among larger, more research-intensive universities.

The other interesting result here is the high significance of the CPP/FCSm from grant for the D2 universities. This is the first time that this variable has been significant. However, at first, the positive sign seems inconsistent with the prediction of the theoretical model. Rather than cost-sharing falling as type rises because of a drop in agency minimum requirements, cost-sharing is rising as the university maximums are rising. This would only occur in case 1b of the model, where as $C_L^{\text{MAX}}$ rises, the cost-sharing offer rises. Since there are limited observations on D2, it is possible that if many of the proposals fell into that case, the model would yield this result.
### Table 3.12

**Fixed Effects Cost-Sharing Model, by Carnegie Classification**

<table>
<thead>
<tr>
<th></th>
<th>(15) Carnegie Class R1 Cost-sharing %</th>
<th>(16) Carnegie Class R2 Cost-sharing %</th>
<th>(17) Carnegie Class D1 Cost-sharing %</th>
<th>(18) Carnegie Class D2 Cost-sharing %</th>
<th>(19) Carnegie Class D2 with Proposals/NSF Budget Cost-sharing %</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CPP/FCSm from grant (“TYPE”)</strong></td>
<td>-0.0237 (0.0290)</td>
<td>0.1393 (0.5373)</td>
<td>1.1713 (1.2107)</td>
<td>1.5755 ** (0.4769)</td>
<td>1.0062 ** (0.3786)</td>
</tr>
<tr>
<td><strong>Publications from grant (“TYPE”)</strong></td>
<td>0.0399 (0.0349)</td>
<td>0.0505 (0.1820)</td>
<td>0.3085 (0.2765)</td>
<td>0.0397 (0.3789)</td>
<td>-0.1997 (0.3655)</td>
</tr>
<tr>
<td><strong>Equipment $ (000’s)</strong></td>
<td>-0.0003 (0.0003)</td>
<td>-0.0014 (0.0037)</td>
<td>-0.0044 (0.0085)</td>
<td>0.0116 (0.0264)</td>
<td>0.0294 (0.0319)</td>
</tr>
<tr>
<td><strong>Research Experience (years)</strong></td>
<td>0.0555 (0.0341)</td>
<td>0.1920 (0.1346)</td>
<td>0.0001 (0.3682)</td>
<td>0.3397 (0.2888)</td>
<td>0.3433 (0.2912)</td>
</tr>
<tr>
<td><strong>CPP/FCSm before grant</strong></td>
<td>-0.0199 (0.0720)</td>
<td>0.3676 (0.4982)</td>
<td>-1.4750 (0.9346)</td>
<td>-1.1090 (2.2131)</td>
<td>-1.0439 (2.3200)</td>
</tr>
<tr>
<td><strong>NRC Dept. Rating</strong></td>
<td>1.4872 ** (0.2676)</td>
<td>2.4822 ** (1.1534)</td>
<td>4.7130 (3.1750)</td>
<td>8.5305 (8.5305)</td>
<td>-13.3507 (11.3623)</td>
</tr>
<tr>
<td><strong>Total Award $ (’000s)</strong></td>
<td>-0.0001 (0.0002)</td>
<td>-0.0035 (0.0041)</td>
<td>-0.0094 (0.0171)</td>
<td>-0.0048 (0.0075)</td>
<td>0.0007 (0.0061)</td>
</tr>
<tr>
<td><strong>F-value (variables of interest)</strong></td>
<td>32.3753 (p = 0.0000)</td>
<td>6.9347 (p = 0.0000)</td>
<td>2.1657 (p = 0.0732)</td>
<td>3.4343 (p = 0.0132)</td>
<td>7.5529 (p = 0.0002)</td>
</tr>
<tr>
<td><strong>Proposals/NSF Budget</strong></td>
<td>-0.0086 (0.2157)</td>
<td>-0.3823 (0.6151)</td>
<td>14.9230 (12.2656)</td>
<td>-7.9676 (7.8808)</td>
<td>-0.9527 (9.2531)</td>
</tr>
<tr>
<td><strong>Fixed Effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>---Directorate</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>F-value (full model)</strong></td>
<td>64.6284 (p = 0.0000)</td>
<td>10.8462 (p = 0.0000)</td>
<td>4.8602 (p = 0.0004)</td>
<td>8.2259 (p = 0.0000)</td>
<td>18.6893 (p = 0.0000)</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>949</td>
<td>149</td>
<td>37</td>
<td>33</td>
<td>33</td>
</tr>
<tr>
<td><strong>R-squared</strong></td>
<td>0.4687</td>
<td>0.4702</td>
<td>0.7285</td>
<td>0.8075</td>
<td>0.8694</td>
</tr>
</tbody>
</table>

Note: * indicates significance at the .10 level and ** indicates significance at the .05 level. Heteroskedasticity-consistent standard errors are shown in parentheses. The F value for the Chow test was 3.5394 with a p value of 0.0000.
The models in Table 3.12 were run without year fixed effects because the D1 and D2 Carnegie schools had many missing values for years. Referring back to Table 3.10, columns 13 and 14 look at replacement alternatives for the year dummies that will allow us to control for agency threshold. In 13, NSF budget in real dollars is highly significant and positive. For a $1 million rise in budget, cost-sharing rises by .0029%. Column 14 shows that another measure of agency threshold, proposals received divided by NSF budget, is marginally significant and negative. Both of these imply that cost-sharing will rise in a loosening budget environment. To try to understand this result, I ran an auxiliary regression of a simple time trend variable on cost-sharing. The time trend coefficient was .327, with standard error of .144. A simple t-test shows the coefficient to be significant at the .023 level of significance. In other words, cost-sharing was increasing over time. Since budgets were also increasing over time, or alternatively proposals/budget were falling over time (see Table 3.2), these alternatives are just serving as a proxy for this time trend in the above models 13 and 14 in Table 3.11. Thus, they could serve as suitable substitutes for year fixed effects. Table 13.12, column 19, attempts to replicate the results in column 18, after including the additional control for time through the Proposal/NSF budget mechanism. The substitute seems to be working well, picking up the heterogeneity across time. Despite controlling for this, the variable for type is still positive and significant. This brings into question the prediction from the theoretical model that cost-sharing will fall as type rises. It appears here that these lower Carnegie Class universities are willing to cost-share more for higher type projects. Perhaps this reflects an effort on their part to try to put an emphasis on guaranteeing NSF’s support for their higher type projects seeking awards.
Let me return now to Table 3.8 and look further into the effect of the removal of the NSF field dummies. Comparing columns 5 & 6 from Table 3.9 to the full model introduced in Table 3.8, I find similar results. NRC department is again marginally significant and has almost the identical impact on cost-sharing. Also, total award is still marginally significant and almost identical in impact. In columns 7 & 8, the removal of the year dummies completely removes the effect of NRC on cost-share %, but the almost identical relationship between total award and total cost-sharing remains.

Table 3.13 presents the results of some other alternative ways of looking at the data set. It explores whether a breakdown by NSF Directorate can be used to shed light on the variable relationships. Looking at the CISE and ENG, some interesting new results come to the surface. For CISE, CPP/FCSm before grant becomes highly significant. This variable was one of the preliminary assessment factors predicted to have this negative relationship with cost-sharing. For every increase in 1 in this field adjusted citation per publication score, cost-sharing % falls by .1764. For ENG, for the first time, total award is a significant factor in determining cost-share % and it is negative. For every $1000 increase in award size, cost-sharing is predicted to fall by .015%. Also, again we see an example of the public university having a positive impact on cost-sharing.
Table 3.13

Fixed Effects Cost-Sharing Model, by NSF Directorate

<table>
<thead>
<tr>
<th></th>
<th>(20) Cost-sharing %</th>
<th>(21) Cost-sharing %</th>
<th>(22) Cost-sharing %</th>
<th>(23) Cost-sharing %</th>
<th>(24) Cost-sharing %</th>
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</thead>
<tbody>
<tr>
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<td>MPS</td>
<td>GEO</td>
<td>CISE</td>
<td>ENG</td>
<td>BIO</td>
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<tr>
<td>CPP/FCSm from grant</td>
<td>0.0063 (0.0418)</td>
<td>-0.1362 (0.3309)</td>
<td>-0.0175 (0.0467)</td>
<td>-0.0060 (0.2351)</td>
<td>0.0603 (0.3096)</td>
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<td>(“TYPE”)</td>
<td></td>
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<tr>
<td>Publications from grant</td>
<td>-0.0222 (0.0570)</td>
<td>-0.0389 (0.1446)</td>
<td>0.0297 (0.0436)</td>
<td>0.2872 (0.1968)</td>
<td>-0.0199 (0.1118)</td>
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<tr>
<td>(“TYPE”)</td>
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<tr>
<td>Equipment $ (000’s)</td>
<td>-0.0003 (0.0004)</td>
<td>-0.0009 (0.0024)</td>
<td>0.0001 (0.0007)</td>
<td>-0.0003 (0.0017)</td>
<td>-0.0006 (0.0005)</td>
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</tr>
<tr>
<td>Research Experience (years)</td>
<td>0.0536 (0.0451)</td>
<td>0.0412 (0.0658)</td>
<td>-0.0428 (0.0906)</td>
<td>0.0108 (0.0907)</td>
<td>0.0780 (0.1358)</td>
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</tr>
<tr>
<td>CPP/FCSm before grant</td>
<td>0.1130 (0.1531)</td>
<td>-0.3118 (0.3316)</td>
<td>-0.1764** (0.0514)</td>
<td>0.1263 (0.1746)</td>
<td>0.2978* (0.1763)</td>
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<tr>
<td>NRC Dept. Rating</td>
<td>-0.6509 (0.9707)</td>
<td>0.1344 (0.9320)</td>
<td>1.6534 (1.1917)</td>
<td>1.0192 (1.3240)</td>
<td>0.4772 (1.4980)</td>
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<tr>
<td></td>
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</tr>
<tr>
<td>Total Award $ ('000s)</td>
<td>0.0000 (0.0002)</td>
<td>0.0013 (0.0011)</td>
<td>0.0021 (0.0017)</td>
<td>-0.0150** (0.0052)</td>
<td>-0.0007 (0.0008)</td>
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</tr>
<tr>
<td>F-value (variables of interest)</td>
<td>0.5974 (p=0.7581)</td>
<td>0.5188 (p=0.8191)</td>
<td>2.2277 (p=0.0337)</td>
<td>1.3123 (p=0.2455)</td>
<td>1.1675 (p=0.3252)</td>
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<tr>
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</tr>
<tr>
<td>Public DV (=1 if public university)</td>
<td>0.6784 (1.1466)</td>
<td>2.3246 (1.7845)</td>
<td>2.3851 (1.9682)</td>
<td>5.9974** (2.0464)</td>
<td>1.8287 (1.9746)</td>
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<tr>
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</tr>
<tr>
<td>λ</td>
<td>0.0280 (.3436)</td>
<td>0.006 (0.329)</td>
<td>-0.3525 (0.5821)</td>
<td>-0.6409 (0.5348)</td>
<td>-0.4713 (0.3409)</td>
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<td>Fixed Effects</td>
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<tr>
<td>--- University</td>
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<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
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<td>--- Field</td>
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<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>--- Carnegie Class</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>--- Year</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>F-value (full model)</td>
<td>23.8188 (p = 0.0000)</td>
<td>6.6102 (p = 0.0000)</td>
<td>10.7309 (p = 0.0000)</td>
<td>13.4426 (p = 0.0000)</td>
<td>6.8097 (p = 0.0000)</td>
</tr>
<tr>
<td>N</td>
<td>404</td>
<td>154</td>
<td>211</td>
<td>238</td>
<td>161</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.5234</td>
<td>0.4967</td>
<td>0.5671</td>
<td>0.5554</td>
<td>0.5329</td>
</tr>
</tbody>
</table>

Note: * indicates significance at the .10 level and ** indicates significance at the .05 level. Heteroskedasticity-consistent standard errors are shown in parentheses. The F value for the Chow test was 2.6475 with a p value of 0.0000.
Table 3.14

Fixed Effects Cost-Sharing by Year

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>CPP/FCSm from grant (“TYPE”)</td>
<td>-0.1730 ** (0.0874)</td>
<td>-0.0374 (0.0592)</td>
<td>0.2211 (0.2633)</td>
<td>-0.0020 (0.0952)</td>
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<tr>
<td>Publications from grant (“TYPE”)</td>
<td>-0.0078 (0.0956)</td>
<td>0.0090 (0.0696)</td>
<td>0.0098 (0.0594)</td>
<td>0.0301 (0.0637)</td>
</tr>
<tr>
<td>Equipment (’000s)</td>
<td>-0.0009 (0.0008)</td>
<td>0.0005 (0.0005)</td>
<td>-0.0006 (0.0005)</td>
<td>-0.0005 (0.0010)</td>
</tr>
<tr>
<td>Research Experience (years)</td>
<td>-0.1783 ** (0.0814)</td>
<td>0.0889 (0.0597)</td>
<td>0.0690 (0.0612)</td>
<td>0.0405 (0.0692)</td>
</tr>
<tr>
<td>CPP/FCSm before grant</td>
<td>0.0597 (0.1445)</td>
<td>0.0495 (0.1499)</td>
<td>-0.1847 * (0.1003)</td>
<td>-0.1569 (0.1301)</td>
</tr>
<tr>
<td>NRC Dept. Rating</td>
<td>5.4393 ** (1.6822)</td>
<td>-1.0868 (0.8279)</td>
<td>0.5243 (1.1375)</td>
<td>1.0197 (0.9314)</td>
</tr>
<tr>
<td>Total Award (’000s)</td>
<td>-0.0001 (0.0007)</td>
<td>-0.0011 (0.0007)</td>
<td>0.0001 (0.0001)</td>
<td>-0.0005 (0.0010)</td>
</tr>
<tr>
<td>F-value (variables of interest)</td>
<td>2.1009 (p=0.0483)</td>
<td>0.8279 (p=0.5646)</td>
<td>0.8679 (p=0.5323)</td>
<td>0.5148 (p=0.8233)</td>
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<tr>
<td>Public DV (=1 if public university)</td>
<td>3.6450* (2.0100)</td>
<td>1.8302 (1.2911)</td>
<td>4.5623 ** (1.8551)</td>
<td>1.3060 (1.6039)</td>
</tr>
<tr>
<td>EPSCoR DV (=1 if EPSCoR)</td>
<td>3.3824 (2.8067)</td>
<td>5.9051 ** (2.7288)</td>
<td>-0.3715 (2.6064)</td>
<td>2.2683 (2.9860)</td>
</tr>
<tr>
<td>λ</td>
<td>0.6237 (0.3770)</td>
<td>-0.4809 * (0.2560)</td>
<td>-0.5222 ** (0.1901)</td>
<td>0.4666 (0.5993)</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>---Carnegie Class</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>---Directorate</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>F-value (full model)</td>
<td>8.5735 (p = 0.0000)</td>
<td>20.3943 (p = 0.0000)</td>
<td>18.5091 (p = 0.0000)</td>
<td>20.2636 (p = 0.0000)</td>
</tr>
<tr>
<td>N</td>
<td>139</td>
<td>380</td>
<td>314</td>
<td>335</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.6008</td>
<td>0.4751</td>
<td>0.5112</td>
<td>0.5238</td>
</tr>
</tbody>
</table>

Note: * indicates significance at the .10 level and ** indicates significance at the .05 level. Heteroskedasticity-consistent standard errors are shown in parentheses. The F value for the Chow test was 1.6703 with a p value of 0.0025.

From Table 3.14, we can see some interesting results that lend support to the theoretical model, especially for 1993-94 and 1997-98 periods. The variable for type is significant and has a
negative sign, giving support to the idea that an increase in type will result in lower cost-sharing. Also, an increase in research experience by 1 year leads to a decrease of .173% in cost-sharing. Finally, note that NRC department is strongly significant and the public/private dummy is marginally significant. For 1997-98, we see an example of a marginally significant negative relationship between a preliminary assessment variable and the cost-sharing percent. This lends some minor support to the hypothesis that there is a tradeoff between proposal quality and cost-sharing.

Table 3.15 reports the results of dividing the sample by NRC ranking. For the proposals coming from the top one-third of NRC departments in the sample, an increase in ranking by 1 point is expected to yield a 1.77% increase in cost-sharing. This same significant result is found with proposals from the bottom one-third of NRC departments, but with a 2.08% effect on cost-sharing. For the lower third, the public/private dummy is highly significant, underscoring this consistent result we have seen across all formulations of the model. Finally, for the second time, we see evidence of cost-sharing percentage being negatively impacted by total award, although the effect is very small at only .0028%.
Table 3.15

Fixed Effects Cost-Sharing by NRC Rating Subsets

<table>
<thead>
<tr>
<th></th>
<th>(29) Highest 1/3 NRC Rating Cost-Share %</th>
<th>(30) Lowest 1/3 NRC Rating Cost-Share %</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPP/FCSm from grant (&quot;TYPE&quot;)</td>
<td>-0.0765 (0.0778)</td>
<td>-0.0438 (0.1655)</td>
</tr>
<tr>
<td>Publications from grant (&quot;TYPE&quot;)</td>
<td>-0.0013 (0.0684)</td>
<td>0.0760 (0.0664)</td>
</tr>
<tr>
<td>Equipment $ (’000s)</td>
<td>-0.0004 (0.0004)</td>
<td>0.0008 (0.0011)</td>
</tr>
<tr>
<td>Research Experience (years)</td>
<td>0.0098 (0.0484)</td>
<td>0.0834 (0.0885)</td>
</tr>
<tr>
<td>CPP/FCSm before grant</td>
<td>0.0935 (0.1750)</td>
<td>-0.1196 (0.1200)</td>
</tr>
<tr>
<td>NRC Dept. Rating</td>
<td>1.7692 ** (0.4148)</td>
<td>2.0777 ** (0.8465)</td>
</tr>
<tr>
<td>Total Award (’000s)</td>
<td>-0.0004 (0.0006)</td>
<td>-0.0028 ** (0.0012)</td>
</tr>
<tr>
<td>F-value (variables of interest)</td>
<td>9.8810 (p=0.0000)</td>
<td>3.6769 (p=0.0008)</td>
</tr>
<tr>
<td>Public DV (=1 if public univ.)</td>
<td>0.0480 (1.0327)</td>
<td>6.7063 ** (1.3797)</td>
</tr>
<tr>
<td>λ</td>
<td>-0.2437 (0.2065)</td>
<td>-0.4997 (0.5901)</td>
</tr>
</tbody>
</table>

Fixed Effects

---Directorate: Yes
F-value (full model): 23.1881 (p = 0.0000)  28.5729 (p = 0.0000)
N: 381  354
R-squared: 0.4516  0.5282

Note: * indicates significance at the .10 level and ** indicates significance at the .05 level. Heteroskedasticity-consistent standard errors are shown in parentheses. The F value for the Chow test was 4.9728 with a p value of 0.0000.

Finally, Table 3.16 notes that other measures for type were tried as potential substitutes. A comparison of the results with the full model in Table 3.8 shows no improvement and lends additional support to the use of CPP/FCSm along with publications from grant.
## Table 3.16

**Fixed Effects Cost-Sharing Full Models with Alternative Citation Measures**

<table>
<thead>
<tr>
<th></th>
<th>(31) Full Model with h-index Cost-Share %</th>
<th>(32) Full Model with CPP Cost-Share %</th>
<th>(33) Full Model with Total Citations Cost-Share %</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPP/FCSm from grant (“TYPE”)</td>
<td>-0.0015 (0.0339)</td>
<td>-0.0005 (0.0082)</td>
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<tr>
<td>CPP from grant (“TYPE”)</td>
<td>-0.0005 (0.0082)</td>
<td>-0.0003 (0.0009)</td>
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<tr>
<td>Citations from grant (“TYPE”)</td>
<td>-0.0177 (0.0369)</td>
<td>-0.0180 (0.0366)</td>
<td>-0.0116 (0.0449)</td>
</tr>
<tr>
<td>Publications from grant (“TYPE”)</td>
<td>-0.0002 (0.0004)</td>
<td>-0.0002 (0.0004)</td>
<td>-0.0002 (0.0004)</td>
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<td>Equipment $ (’000s)</td>
<td>-0.0011 (0.0443)</td>
<td>0.0071 (0.0353)</td>
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<td>Research Experience (years)</td>
<td>0.0086 (0.0324)</td>
<td>0.0120 (0.0153)</td>
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</tr>
<tr>
<td>h-index before grant</td>
<td>0.0086 (0.0324)</td>
<td>0.0120 (0.0153)</td>
<td>0.0001 (0.0001)</td>
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<tr>
<td>CPP before grant</td>
<td></td>
<td>0.0120 (0.0153)</td>
<td></td>
</tr>
<tr>
<td>Total Citations before grant</td>
<td></td>
<td>0.0001 (0.0001)</td>
<td></td>
</tr>
<tr>
<td>NRC Dept. Rating</td>
<td>0.9738 * (0.6028)</td>
<td>0.9153 (0.6031)</td>
<td>0.9760 * (0.6028)</td>
</tr>
<tr>
<td>Total Award (’000s)</td>
<td>-0.0002 (0.0002)</td>
<td>-0.0002 (0.0002)</td>
<td>-0.0002 (0.0002)</td>
</tr>
<tr>
<td>F-value (variables of interest)</td>
<td>0.5725 (p=0.7787)</td>
<td>0.6507 (p=0.7140)</td>
<td>0.6383 (p=0.7244)</td>
</tr>
<tr>
<td>λ</td>
<td>0.8352 (0.5148)</td>
<td>0.8196 (0.5128)</td>
<td>0.8243 (0.5164)</td>
</tr>
</tbody>
</table>

### Fixed Effects

--- University: Yes, Yes, Yes, Yes
--- Field: Yes, Yes, Yes
--- Year: Yes, Yes, Yes

F-value (full model):
- (31) 14.1008 (p = 0.0000) 13.6840 (p = 0.0000) 14.0276 (p = 0.0000)
- (32) 1168                     1168                     1168
- (33) 0.6139                   0.6143                   0.6140

Note: * indicates significance at the .10 level and ** indicates significance at the .05 level. Heteroskedasticity-consistent standard errors are shown in parentheses.
CHAPTER 4
CONCLUSIONS AND RECENT COST-SHARING POLICY CHANGES AT NSF

4.1 Summary and Conclusions

The theoretical model of cost-sharing developed in Chapter 2 shows that the type of cost-sharing outcome is dependent on the thresholds of the agency and university. During times when the agency has a large pool of money available relative to the proposals submitted, the agency’s threshold is lower, i.e. the required expected net benefit from proposal’s research is lower. For the researcher, plentiful university or department budgets mean lower thresholds, which is equivalent to higher amounts of cost-sharing that the university would be willing to pay for a particular project. During times when agency and or university thresholds are lower, it is more likely for a pooling equilibrium to result in which both low and high types are funded and at an equal cost-sharing level. Given the uncertainty about true type, the agency will use information available to assess the probability of the project being a high type. In this environment, it was shown in the theoretical model that funded proposals increased cost-sharing to compensate for low preliminary assessments. The empirical model tested in chapter 3 provided some limited evidence of this relationship. When the model was run for the time period 1993-94, both NRC department and research experience had significant, negative impacts on cost-sharing. However, these results were not typical. Rather, it seems that NRC department is better described as a
measure of the threshold of the researcher’s department. Under several formulations of the model, NRC had a positive impact on cost-sharing. Also, research experience generally had a positive impact on cost-sharing as well. This is not consistent with our prior expectations or the 1993-1994 period, but can be understood if research experience is a proxy for the threshold for a particular researcher. When the sample was divided by research experience, we saw that for veteran researchers, cost-sharing rises with even greater research experience. Finally, the university effects and the public/private dummy were very strongly related to cost-sharing. Here, it is a measure of university threshold that seems important. These three results suggest that threshold can vary by researcher, department, and university and it is these thresholds that determine the willingness to cost-share on the university’s behalf and thus, the resulting cost-sharing level observed.

As funding environments tighten for either the agency or university, the theoretical model predicted that a separating equilibrium would result. In this environment, only high types apply and are funded at the agency’s cost-sharing minimum for high types. The model also found that the greater the research output expected from the high type project, the smaller that the cost-sharing offer needed to be. There was very little evidence of this relationship in the empirical model, with the exception of model 14 where CPP/FCSm was highly significant in one of the year pairings.

One of the traditional justifications for the use of cost-sharing in the federal funding of academic research is an equity argument. Since universities accrue real, monetary gains from research,
either directly from the generation of patent revenues or indirectly from the gaining of increased prestige that translates into increased tuition revenues or more external research funding, they should be required to pay their fair share of the costs. The focus of this thesis was another potential justification for the use of cost-sharing, that cost-sharing provides information to the funding agency about the quality of the proposal. The theoretical model predicted that in some funding environments, cost-sharing would allow the agency to weed out low type projects, leaving only high type projects in the proposal competition. Under looser agency budget environments, lower type projects could apply and be funded, but higher cost-sharing commitments would be required from all proposals which had lower preliminary assessments. The empirical section provided very minimal evidence that cost-sharing varies negatively with the preliminary assessment. This includes evidence from the 1993-1994 period, some marginal evidence from the 1997-98 period, and the relationship between total cost-sharing and grant award. We cannot conclude with any certainty that there is traditional signaling in the model on the basis of limited empirical support of the theoretical prediction. However, it seems that greater cost-sharing is a function of the threshold of the project, whether this threshold derives from the university, department, or researcher level characteristics. This is supportive of the traditional leveraging explanation of cost-sharing. Agencies seem to act in a manner similar to that of a price-discriminating monopolist, requiring varying levels of cost-sharing (or “prices”) based on the ability of the proposer to provide cost-sharing. There was also evidence that cost-sharing was also determined by the agency’s threshold, which varied over time and across field or directorate. Thus, the degree to which leveraging was used seemed to vary by these characteristics as well.
4.2 Recent Changes in Cost-Sharing Policy at NSF

As described earlier in the dissertation, in response to growing pressure from universities over cost-sharing policies, NSF moved in 1999 to limit cost-sharing practices. In 2004, they went a step further, eliminating all program specific cost-sharing and removing it from the proposal review process entirely by masking any voluntary cost-sharing from reviewers. Thomas Cooley, current chief financial officer of NSF, predicted that the 2004 changes would have two effects. They would make it easier for smaller universities to compete for awards, but also reduce the number of solicited awards it offers since the foundation would be paying the entire cost of the project (Field, 2004).

Despite only a few years passing since these changes were put into place, there is enough data available to observe what the initial impacts have been. Table 4.1 shows that there has been a downward trend in funding rates since 2000 for the categories of grants and all awards. At first glance, it seems that this may be the result of NSF cutting back on awards because of the drop in cost-sharing. However, during the same period, the number of proposals received rose from 29,407 in FY 2000 to 44,577 in FY 2007 (NSF, 2008c). This is a dramatic increase, considering the number of proposals remained relatively stable between 1993 and 2000, beginning the period at 30,003 (NSF, 2000). Perhaps the dropping of the cost-sharing requirements encourage a wider range of researchers and universities to participate in the process.
Table 4.1

NSF Funding Rates

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<th>2000</th>
<th>2001</th>
<th>2002</th>
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<th>2004</th>
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<th>2006</th>
<th>2007</th>
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<tr>
<td><strong>All Award Types</strong></td>
<td>33%</td>
<td>31%</td>
<td>30%</td>
<td>27%</td>
<td>24%</td>
<td>23%</td>
<td>25%</td>
<td>26%</td>
</tr>
<tr>
<td><strong>Grants</strong></td>
<td>30%</td>
<td>27%</td>
<td>27%</td>
<td>24%</td>
<td>21%</td>
<td>20%</td>
<td>21%</td>
<td>22%</td>
</tr>
</tbody>
</table>

We can also explore the initial impacts of the NSF cost-sharing policy changes on the dispersion of funding across universities. Figure 4.1 displays the Lorenz curves for the top 200 universities in terms of federal research & development obligations made by NSF in years 1997-98 (pre-changes) and years 2004-2005 (post-changes) (NSF, 2008a). Comparing the results shows that the share of funding held by the top universities remained virtually unchanged. The Gini coefficients for the 2 periods were equal to .585 in 1997-98 and .586 in the 2004-05 period. Looking at some subsamples of the top 200, the top 30 universities garnered 51.50% of the funding received by the top 200 in the 1997-98 period and 51.04% in the 2004-05 period. The bottom 30 universities received 1.64% of the funding in the earlier period compared to 1.52% in the later period. This does not provide evidence of a leveling of the playing field that was predicted to be result from the cost-sharing changes.
We may never know what the full impacts of the drop in cost-sharing would have been over a longer time period, because in August, 2007, another sea change occurred with respect to cost-sharing policy. As a result of the passage of the America Competes Act, the National Science Foundation was directed to undertake a review of the impacts of the 2004 cost-sharing changes. The initial report in response to this directive led to the National Science board recommending the reinstatement of cost-sharing in award competitions that previously involved significant cost-sharing levels. These included large programmatic awards and awards involving
university/industry partnerships. The Board also plans to release another report in the second half of 2008 offering further recommendations with regard to the wider use of voluntary cost sharing (National Science Foundation 2008b).

Given that there is at least there is some evidence of informational value in the cost-sharing message sent during funding proposal process, we cannot say that the changes implemented in the early part of this decade changed the efficient allocation of research dollars. Future efforts to re-evaluate cost-sharing policy should consider the potential for the informational value of cost-sharing along with other justifications and criticisms. Given that science and engineering research is such a vital input to economic growth and advancement of the workforce, the allocation of scarce federal funds needs to be made in the most efficient manner possible. Seeing cost-sharing only as a way to leverage more projects, thus overlooking the potential for cost-sharing to assist in this resource allocation process, could have negative consequences for the technological future of the U.S.
What follows is an extension of the theoretical model presented in Chapter 2. Two primary assumptions that were made in Chapter 1 to allow for the study of a clear set of testable conclusions will be relaxed here. First, it was assumed that the statutory cost-sharing level, $C$, was fixed at a low level. Here, $C$ will be allowed to vary and we will observe the resulting outcomes when this occurs. Second, it was assumed that cost-sharing only occurs at the proposal stage. In other words, there was no other opportunity for cost-sharing to rise above what was stated in the proposal when originally submitted. However, as described in Chapter 1, cost-sharing can occur during the proposal review process as part of pre-award negotiations. This second stage of cost-sharing will be modeled as a take-it-or-leave-it counteroffer made by the agency. The motive of the agency here is to extract further rents from the university. This counteroffer, $C_2$, will be given by:

$$C_2 = (1+t) C_1$$  \hspace{1cm} (A.1a)

where $0 \leq t \leq 1$

The factor $t$ represents the relative bargaining power of the agency. Also, $t = f (X_A)$ and is increasing in $X_A$. So in times when the agency budget constraint is tight or there are many proposals competing for the same funds, $X_A$ is higher and agencies make a higher counter-offer. If agencies are awash in funds for research support, the threshold for which projects to accept is lower, and consequently, the factor $t$ will be low or maybe even zero, implying no counter-offer.
This counteroffer is then accepted by the university (and therefore the project is funded) as long as the new cost-sharing level does not exceed its maximum willingness-to-pay. In cases where the agency remains uncertain of type after receiving the original cost-sharing message, the counter-offer will be at least high enough that the expected net payoff satisfies its own threshold. In the event that the original message is already at a type’s maximum and the first stage offer satisfied the agency’s participation constraint, no counteroffer is made and the proposal is accepted on its face.

A.1 Solving for the Equilibria

This section will be concerned with finding both pooling and separating equilibria in the static model when there are only two types of proposals being submitted. It will be shown that the resulting equilibria will depend on characteristics of the university (i.e. its payoff function, threshold value, \(X_U\), and miscellaneous observable characteristics that affect the distribution from which type is drawn), the characteristics of the agency (i.e. its threshold value, \(X_A\)), and the amount of the grant being offered (\(G\)). Before proceeding, a number of definitions will be reviewed:

\[
C_{H}^{\text{MAX}} = \Pi[\Psi(H)] - X_U \quad \text{(A.1b)}
\]

\[
C_{L}^{\text{MAX}} = \Pi[\Psi(L)] - X_U \quad \text{(A.1c)}
\]

where \(C_{H}^{\text{MAX}}\) and \(C_{L}^{\text{MAX}}\) are the values of \(C\) in which the participation constraints for the high
and low type applicants hold with equality. The participation constraint for the agency, in terms of $C$, is given in the following inequality:

$$C \geq X_A - \Psi(T) + G \quad \text{(A.1d)}$$

Thus, for a high type applicant, the value of $C$ in which A.1d is just binding is:

$$C_{AH}^{\text{MIN}} \equiv X_A - \Psi(H) + G \quad \text{(A.1e)}$$

and for the low type applicant, it is:

$$C_{AL}^{\text{MIN}} \equiv X_A - \Psi(L) + G \quad \text{(A.1f)}$$

It is also useful to note the amount of 1st stage cost-sharing that results in these $C^{\text{MIN}}$ for each type. For the high type, this will be defined as:

$$\hat{C}_{AH} \equiv \frac{C_{AH}^{\text{MIN}}}{1+t} \quad \text{(A.1g)}$$

For the low type define:

$$\hat{C}_{AL} \equiv \frac{C_{AL}^{\text{MIN}}}{1+t} \quad \text{(A.1h)}$$

We can also conclude that it is always the case that $C_{H}^{\text{MAX}} > C_{L}^{\text{MAX}}$ and that $C_{AH}^{\text{MIN}} < C_{AL}^{\text{MIN}}$.

Figure A.1 shows the three possible general cases that might occur, depending on the size of $C$ in
relation to $C_L^{\text{MAX}}$ and $C_H^{\text{MAX}}$. 

FIGURE A.1

Case 1

<p>| | | | |</p>
<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>$C_L^{\text{MAX}}$</td>
<td>$C_H^{\text{MAX}}$</td>
<td>$C$</td>
<td>$G$</td>
</tr>
</tbody>
</table>

Case 2

<p>| | | | |</p>
<table>
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<tr>
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</thead>
<tbody>
<tr>
<td>$C_L^{\text{MAX}}$</td>
<td>$C$</td>
<td>$C_H^{\text{MAX}}$</td>
<td>$G$</td>
</tr>
</tbody>
</table>

Case 3

<p>| | | | |</p>
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<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$C$</td>
<td>$C_L^{\text{MAX}}$</td>
<td>$C_H^{\text{MAX}}$</td>
<td>$G$</td>
</tr>
</tbody>
</table>
A.1.1 Case 1: $C_l^{MAX} < C_H^{MAX} < C$ ("Full Screening Case")

Here, the cost-sharing requirement in the proposal announcement is so large that neither low nor high types will apply. The size of this $C$ does not imply that zero proposals will be funded. For other universities with lower threshold values $X_U$ (e.g. a larger university may have larger research budgets or any university may have devoted a sizable budget to this research area.), the higher maximum cost-share amounts will change this to a case 2 or case 3 problem, where funding can occur.

A.1.2 Case 2: $C_l^{MAX} < C < C_H^{MAX}$ ("Partial Screening Case")

In this case, low types will never find it rational to apply. Therefore when a proposal is observed, the agency’s beliefs are updated to the probability of high type equal to one. In this case the high type is free to offer just enough to satisfy the agency’s participation constraint for a high type proposal. Since this constraint only needs to be satisfied when the final cost-sharing terms are worked out (i.e. after the 2nd stage counter-offer), the university takes this into account and makes an offer $C_H^1 = \max \{\hat{C}_{AH}, C\}$. However, because this offer may not be consistent with the university’s participation constraint, there are 2 sub-cases to consider.

Case 2A: $\Pi[\Psi(H)] - C_H^1(1+t) \geq X_U$

This is equivalent to $C_H^1(1+t) \leq C_H^{MAX}$, implying the first stage cost-sharing offer that meets the agency’s participation constraint also produces a counteroffer acceptable to the university. Thus, the best response of the high type to offer $C_H^1 = \max \{\hat{C}_{AH}, C\}$. The counter-offer, $C^2$, equals $C_H^1(1+t)$. An interesting aspect to this case, is that when low types are screened out by the
statutory requirement, high types can effectively make a lower first stage offer since
\[ \hat{C}_{AH} < p \hat{C}_{AH} + (1-p) \hat{C}_{AL}. \]
We will define the right hand side of this inequality to facilitate its further use in future cases:

\[ \hat{C}_A = p \hat{C}_{AH} + (1-p) \hat{C}_{AL} \quad (A.1i) \]

Intuitively, \( \hat{C}_A \) indicates the stage one offer that is expected to just satisfy the agency’s participation constraint when the prior beliefs about type are unchanged after receiving the cost-sharing message.

**Case 2B:** \( \Pi[\Psi(H)] - C_{H}^1(1+t) < X_{U} \). In this case, the value of \( C_{H}^1 \), which satisfies the agency’s participation constraint, violates the participation constraint of the university. Thus, there does not exist a level of cost-sharing acceptable to both parties and no application is made. As with case 1, this does not mean that such a statutory requirement rules out any funded proposals, it only implies that universities with these particular threshold values of \( X_{U} \) will not be able to participate in the process.

**A.1.3 Case 3:** \( C < C_{L}^M \) \( < C_{H}^M \) ("No Screening Case")

This is the most complex and interesting of the cases to consider because there are a variety of sub-cases and equilibria to consider. These sub-cases will depend on where \( C_{AH}^{MIN} \) and \( C_{AL}^{MIN} \) fall in relation to \( C_{L}^{MAX} \) and \( C_{H}^{MAX} \). Since in this case both types may apply for the grant, we must now think in terms of both pooling and separating equilibria.
Case 3A.1: $C_{AH}^{MIN} < C_{AL}^{MIN} < C < C_{L}^{MAX} < C_{H}^{MAX}$

**FIGURE A.2**

Case 3A.1

First, consider the potential pooling equilibria. Let us define the stage 1 cost-sharing offer that leads to a counter-offer equal to $C_{H}^{MAX}$ for the high type as:

$$\hat{C}_{UH} = \frac{C_{H}^{MAX}}{(1+t)} \quad \text{(A.1j)}$$

Similarly, for the low type define:

$$\hat{C}_{UL} = \frac{C_{L}^{MAX}}{(1+t)} \quad \text{(A.1k)}$$
It follows from definition A.1k that any $C^1 > \hat{C}_{UL}$ will result in a counter-offer that violates the low type’s participation constraint and thus will never constitute a pooling equilibrium. Any $C^1 \in (C, \hat{C}_{UL}]$, cannot be a pooling equilibrium because both types would want to deviate to a lower $C$. This leaves one potential candidate for a pooling equilibrium, $C^1 = C$. To establish a specific perfect Bayesian equilibrium, one must show:

(i.) The action of the agency, which is the counteroffer (or the rejection of the proposal if $C^1 < C$), is a best response to the pair of strategies, $C_H^*$ and $C_L^*$, given its beliefs about type after receiving the cost-sharing message (call this belief $u(T|C^1)$). Recall that the counter-offer would be a multiple $(1+t)$ of the first stage offer. If the proposal’s type is not known with certainty, then the counteroffer will be the max$\{ (C^1(1+t), C_{A_{MIN}}^1)$\}.\footnote{The method the agency uses in choosing the counteroffer is of course only one of an infinite number of possible methods. For each different method chosen, a different set of pooling and/or separating equilibria may result. This specific method was chosen because it reflects the desire of the agency to extract some additional surplus from the university, thus allowing it to fund more projects. As mentioned earlier, the value of $t$ can vary with the agency’s threshold, $X_A$.}

Finally, note that a proposal is immediately rejected if $C^1 < C$.

and

(ii.) $C_H^*$ and $C_L^*$ are best responses to each other and the agency’s optimal strategy, given $u(T|C)$ for all possible cost-sharing levels.
**Proposition A.1:** $C_H^* = C_L^* = \bar{C}$ is a pooling equilibrium for Case 3A.1 if $C \leq \hat{C}_{UL}$

**Proof:**

Since $C_H^* = C_L^*$, $u(H|C) = p$ and $u(L|C) = 1 - p$. In other words, beliefs are not altered from their priors because both types are equally likely to cost-share at $C$. The counteroffer, $C^2$, equals $(1+t)C$. Because $C$ exceeds $\hat{C}_A$, the agency is at least receiving expected payoff equal to $X_A$.

For both types, clearly $C$ is a best response to this strategy. It will allow them to be funded at the lowest possible level of cost-sharing and receive net benefit above their threshold (we know this since $C \leq \hat{C}_{UL}$, $C(1+t) \leq C_L^{MAX} < C_H^{MAX}$). Because there is no way to offer less and offering more would only decrease their net benefit, there is no incentive to deviate.

If $C > \hat{C}_{UL}$, then the low types will not apply as the counteroffer would exceed $C_L^{MAX}$. In this case only high types apply, $C_H^* = C$ and the counteroffer of $(1+t)C$ is accepted. If $C > \hat{C}_{UH}$, then neither type will apply.

---

17 In fact, any initial offer less than $\hat{C}_{UL}$ will not alter the prior beliefs of the agency, since both types could make such an offer.
**Case 3A.2:** \( C^{MIN}_{AH} < C < C^{MIN}_{AL} < C^{MAX}_{L} < C^{MAX}_{H} \)

**FIGURE A.3**

**Case 3A.2**

| \( C^{MIN}_{AH} \) | \( C \) | \( C^{MIN}_{AL} \) | \( C^{MAX}_{L} \) | \( C^{MAX}_{H} \) | \( G \) |

**Proposition A.2:** If \( \hat{C}_{A} \leq C \), then \( C^{*}_{H} = C^{*}_{L} = C \) is a pooling equilibrium for Case 3A.2.

**Proof:**

For the agency, an offer of \( C \) here will not change the prior beliefs about type because either type could potentially make this offer. Therefore, the counter-offer, \( C^{2} = \max \{(C^{1}(1+t), C_{A}^{MIN}\} \) so that the expected payoff is at least equal to their threshold value. Could the high types offer more, distinguish themselves from the low types, and improve their second period offer? To do so, they would need to make and offer \( C^{1}_{H} > \hat{C}_{UL} \) in order to make the agency update its belief \( u(H|C) = 1 \). The counter-offer would equal \( \max\{(C^{1}(1+t), C_{AH}^{MIN}\} \). Since \( C_{AH}^{MIN} < C \), \( C^{2} = C^{1}(1+t) > C^{MAX}_{L} \). However, this does not benefit the high types because not deviating from the pooling equilibrium yields a higher counter-offer.
**Proposition A.3:** If $\hat{C}_A > \underline{C}$, then $C_H^* = C_L^* = \hat{C}_A$ is a pooling equilibrium for Case 3A.2.

**Proof:**

When the agency receives the cost-sharing offer, it does not alter its prior beliefs about type, because either type could have sent this message. If either type deviates to a lower stage 1 offer, then their proposal would not be funded as the expected payoff for the agency would fall below its threshold.

In Case 3a.2, the high types are penalized by the inclusion of low types in the proposal contest. If there were no low types, they could cost-share at $\underline{C}$ instead. Also note that when the percentage of low type proposals is greater (i.e. $p$ is lower), the equilibrium outcome $\hat{C}_A$ is higher, increasing the cost-sharing burden on the high types even more.

Solving for $\hat{C}_A$ shows:

$$\hat{C}_A = \frac{p [X_A - \Psi(H) + G] + (1-p)[ X_A - \Psi(L) + G]}{(1+ t)} \quad (A.3l)$$

It is interesting to note that the equilibrium cost-sharing will be increasing in $X_A$ and $G$ and decreasing in $\Psi(T)$, $t$, and $p$. So when the vast majority of proposals are high quality (i.e. $p$ is close to 1), initial cost-sharing will be lower for both types, ceteris paribus.
**Case 3A.3:** \( C < C_{AH}^{MIN} < C_{AL}^{MIN} < C_{L}^{MAX} < C_{H}^{MAX} \)

**FIGURE A.4**

Case 3A.3

---

**Proposition A.4:** If \( C \leq \hat{C}_A \) (in cases of low \( p \)), then \( C_H^* = C_L^* = \hat{C}_A \) is a pooling equilibrium for Case 3A.3.

**Proof:**

This level of initial cost-sharing will result in a counter-offer that just makes the agency’s expected payoff exactly equal \( X_A \). Therefore, both proposals would be funded. Neither type could deviate and make a lower offer because this would lead to no funding.
Proposition 2.5: If $C > \hat{C}_A$ (in cases of high $p$), then $C^*_H = C^*_L = C$ is a pooling equilibrium for Case 3A.3.

Proof:
This cost-sharing offer will lead to a counter-offer that exceeds $C^\text{MIN}_A$, i.e. the expected payoff from the project will exceed the agency’s threshold. Therefore, the proposal will be funded. A deviation to a lower cost-sharing level is not possible. High types would prefer if they could distinguish themselves as such by offering a higher first stage offer, but any offer that would make them better off could also have come from the low type. Making the offer higher than what would come from a low type would make them worse off than the $C$ offer.

Comparing the equilibrium result from propositions 2.4 and 2.5 shows the benefits to high types of a greater prior appraisal of the proposal being high type. This would suggest a lower cost-sharing result would be expected when the agency’s pre-judgment of quality is high.
Case 3B: $C < C_{AH}^{MIN} < C_{L}^{MAX} < C_{AL}^{MIN} < C_{H}^{MAX}$

**FIGURE A.5**

Case 3B

![Diagram showing C, C_{AH}^{MIN}, C_{L}^{MAX}, C_{AL}^{MIN}, C_{H}^{MAX}, and G]

**Proposition A.6:** If $C_{A}^{MIN} < C_{L}^{MAX}$ (in cases of high $p$), $C_{H}^{*} = C_{L}^{*} = \max \{ C, \hat{C}_{A} \}$ is a pooling equilibrium for Case 3B.

**Proof:**

At this equilibrium, the counter-offer will satisfy the agency’s participation constraint. Both type of proposals are funded. As we have seen in previous cases, high types would prefer to deviate to a another cost-sharing level that would distinguish itself as a high type. To accomplish this, the high type would need to offer above $\hat{C}_{UL}$. But since $C_{A}^{MIN} < C_{L}^{MAX}$ in this case, $\hat{C}_{UL} > \hat{C}_{A}$. Thus, distinguishing themselves proves too costly to encourage deviation away from the equilibrium.
Proposition A.7: If $C_A^{\text{MIN}} > C_L^{\text{MAX}}$ (in cases of low $p$), there is a separating equilibrium in case 3B in which $C_H^* = \max \{ C, \text{a value trivially higher than } \hat{C}_{UL} \}$. Low types do not apply.

**Proof:**

Because $C_A^{\text{MIN}} > C_L^{\text{MAX}}$, the low types cannot make an offer that satisfies their own participation constraint and is also acceptable to the agency. When high types make an offer higher than $\hat{C}_{UL}$, the agency updates its beliefs to $u(H|C_H^*) = 1$ and funds the project at $(1+t)C_H^*$. If $\hat{C}_{UL} < C$, then at least $C$ will be offered. This is sufficient to drive low types out as well.

Comparing the results of Proposition A.6 and A.7 reveals that higher $p$ results in lower equilibrium cost-sharing strategies. As $p$ falls, the equilibrium $C^*$ rises. This continues until $p$ becomes too low and the low types are driven out. At this point, further increases in $p$ do not raise the cost-sharing by the high type any further.

*Case 3C.1: $C < C_L^{\text{MAX}} < C_{AH}^{\text{MIN}} < C_A^{\text{MIN}} < C_{AL}^{\text{MIN}} < C_H^{\text{MAX}}$

**FIGURE A.6**

Case 3C.1
**Proposition A.8:** There is a separating equilibrium in case 3C.1 in which $C^*_H = \max \{C, \hat{C}_{AH}\}$. Low types do not apply.

**Proof:**

The value of $C^*_H (1+t)$ is high enough that the low type’s participation constraint is violated. Because no low types will apply, the agency updates its beliefs to $u(H|C^*_H) = 1$ and funds the project at $C^*_H (1+t)$. The university cannot offer less than $C^*_H$ as this would violate the agency’s participation constraint and the proposal would no longer be funded. There is no benefit from deviating from $C^*_H$ and offering more cost-sharing.

**Case 3C.2:** $C < C_{L \text{MAX}} < C_{AH \text{MIN}} < C_{H \text{MAX}} < C_{AL \text{MIN}}$

\[\text{FIGURE A.7}\]

\text{Case 3C.2}

\begin{center}
\begin{tikzpicture}
\draw[->] (0,0) -- (5,0);
\draw (0.5,0.3) node {$C$};
\draw (1.5,0.3) node {$C_{L \text{MAX}}$};
\draw (2.5,0.3) node {$C_{AH \text{MIN}}$};
\draw (3.5,0.3) node {$C_{H \text{MAX}}$};
\draw (4.5,0.3) node {$C_{AL \text{MIN}}$};
\end{tikzpicture}
\end{center}

**Proposition A.9:** If $C_{A \text{MIN}} < C_{H \text{MAX}}$ (in cases of low $p$) or if $C_{A \text{MIN}} > C_{H \text{MAX}}$ (in cases of high $p$), there is a separating equilibrium in case 3C.2 in which $C^*_H = \max \{C, \hat{C}_{AH}\}$. Low types do not apply.

**Proof:**

Proof is identical to that of Proposition A.8.
Case 3D: $C_L^\text{MAX} < C_{A_H}^\text{MIN} < C_L^\text{MAX} < C_{A_L}^\text{MIN}$

**Proposition A.10:** Neither high nor low types apply.

**Proof:**

The proof is trivial, since the agency will always counteroffer at least $C_{A_H}^\text{MIN}$, which is a greater amount than either type would be willing to cost-share. This case will never occur in reality because it would imply that the agency would not fund any projects, which goes against its goal of maximum total research. Intuitively, what has happened is that the agency has no funds to award and thus has set its threshold so high that no applicant could ever meet the requirements.
A.2 Discussion and Summary of Results

A general finding common to many of the sub-cases is that the greater the value of p, the less cost-sharing required in equilibrium. This is intuitively sound as p represents the observable factors that the agency would use to predict type. When factors such as the track record of the researcher, the scientific merit score of the proposal, the quality of the department, and the stock of equipment are favorable, the agency will assign a high probability of the project being high type. This leads to a lower cost-sharing level that satisfies the agency’s participation constraint, and thus lower cost-sharing.

When the statutory cost-sharing level, \( C \), is set high enough, the model becomes a screening model, effectively muting the ability of the cost-sharing offer to be a signal. This occurs in cases 1, 2A, and 2B. If the agency could set \( C \) optimally, as in case 2A, they could ensure higher cost-sharing and screen out low type projects. However, since in reality this \( C \) is generally either set for a wide range of proposal announcements or as an agency-wide policy, it would only work for the class of proposals coming from universities with a narrow range of characteristics (so that \( C_L^{\text{MAX}} < C < C_H^{\text{MAX}} \)). Where cost-sharing could become an effective tool from the agency’s perspective is when the statutory requirement is set relatively low, as in case 3, but the agency threshold is set relatively high. In Table 2.1, a summary of results is presented. There are a couple of interesting results to highlight from case 3. First, in most sub-cases of case 3, a university is rewarded for a high value of p through a lower equilibrium cost-share. This suggests that a proposal coming from a department with favorable observable characteristics and from a researcher with a proven track record, will not have to cost share as much to “prove
itself”. Another interesting result of note in case 3 is that there are several sub-cases in which separating equilibria occur and low types are driven out. This does not require the precise selection of a statutory requirement as in case 2a, but the setting of a threshold level at a higher level. Note though that case 3d demonstrates that setting the threshold too high will keep some types of universities (those with high thresholds of their own, maybe due to tight internal budget conditions) out of the funding arena.

Table A.1

Summary of Cases

<table>
<thead>
<tr>
<th>Case</th>
<th>Type of Equilibrium</th>
<th>Description of Equilibrium</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Pooling</td>
<td>“Full Screening”: Neither type applies.</td>
<td></td>
</tr>
<tr>
<td>2A</td>
<td>Separating</td>
<td>“Partial Screening”: Low types do not apply and $C_H^* = \max {C_{AH}, C}$</td>
<td></td>
</tr>
<tr>
<td>2B</td>
<td>Pooling</td>
<td>Neither type applies.</td>
<td></td>
</tr>
<tr>
<td>3A.1</td>
<td>Pooling</td>
<td>“No Screening Case”: $C_H^* = C_L^* = C$</td>
<td></td>
</tr>
<tr>
<td>3A.2</td>
<td>Pooling</td>
<td>$C_H = C_L = \bar{C}$ or $\bar{C}_A$</td>
<td>Greater p implies less equilibrium cost-sharing.</td>
</tr>
<tr>
<td>3A.3</td>
<td>Pooling</td>
<td>$C_H^* = C_L^* = \max {C, \bar{C}_A}$</td>
<td>Greater p implies less equilibrium cost-sharing.</td>
</tr>
<tr>
<td>3B</td>
<td>Pooling Separating</td>
<td>$C_H = C_L = \max {C, \bar{C}<em>A}$ (for high p) Or $C_H^*$ is trivially larger than $\bar{C}</em>{UL}$ and low types do not apply.</td>
<td>Greater p implies less equilibrium cost-sharing.</td>
</tr>
<tr>
<td>3C.1</td>
<td>Separating</td>
<td>$C_H^* = \max {C, \bar{C}_{AH}}$ Low types do not apply.</td>
<td>High types benefit from the elimination of low types.</td>
</tr>
<tr>
<td>3C.2</td>
<td>Separating</td>
<td>$C_H^* = \max {C, \bar{C}_{AH}}$ Low types do not apply.</td>
<td>High types benefit from the elimination of low types.</td>
</tr>
<tr>
<td>3D</td>
<td>Pooling</td>
<td>Neither type applies.</td>
<td></td>
</tr>
</tbody>
</table>

For both types, there does not exist a $C^*$ such that both agency and university participation constraints are satisfied.
REFERENCES


Hare, Paul & Wyatt, Geoffrey (1988) “Modelling the determination of research output in British Universities”. Research Policy. 17: 315-328


National Science Foundation (2008b) *Report to Congress on Cost Sharing Policies at the National Science Foundation*. 104
National Science Foundation (2008c) *Report to the National Science Board on the National Science Foundation’s Merit Review Process: Fiscal Year 2007.*

National Science Foundation (2008d) *Grant Proposal Guide.*


Web of Science (2008) “Science Citation Index”.

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B.A., Economics, minors: Business and Math (Summa cum laude), June 1993, Wittenberg University, Springfield, OH 45501

Thesis: “The Role of Cost-sharing as a Signal of Project Quality in the Federal Funding of Academic Research: An Application to the National Science Foundation” Advisor: Professor N. Edward Coulson

Areas of Concentration:
Primary: Industrial Organization, Public Finance
Secondary: Econometrics

Professional Experience:
Instructor, Graceland University, Fall 2003-current
Courses taught: Introductory Microeconomics (15 sections), Introductory Macroeconomics (8 sections), Intermediate Microeconomics (5 sections), Money & Banking (7 sections), Economics of Sports (4 sections), Public Finance, Managerial Economics (2 sections), Competitive Business Scenarios (2 sections), Graduate Examination Preparation

Instructor, World Campus, The Pennsylvania State University
Introductory Microeconomics (Summer 1996-Summer 2003)

Instructor, Department of Economics, The Pennsylvania State University
Introductory Economics (Spring 1999; Spring 2001)
Introductory Microeconomics (Spring 1998)
Intermediate Macroeconomics (Summer 1997; Fall 1997)
Introductory Macroeconomics (Summer 1996)

Co-instructor, Department of Economics, The Pennsylvania State University
Introductory Economics (Spring 1997; Spring 1998)

Teaching Assistant, Department of Economics, The Pennsylvania State University
Introductory Economics (Spring 2000)
Introductory Microeconomics (Fall 1993; Fall 1996)
Money & Banking (Spring 1994)

Research Assistant, Department of Economics, The Pennsylvania State University
Dr. Irwin Feller (Fall 1994-Spring 1996; Summer 1998-Fall 1999)
Dr. Mark Wilhelm (Summer 1994)

Honors and Awards:

Publications:
Introductory Microeconomic Analysis, 2002 (130+ pg. study guide written for Pennsylvania State University World Campus)

Service:
Member of Council on Student Welfare (2004-current); Chair (Fall 2005-Spring 2007)
Member of General Education Committee (2004-current); Chair (Fall 2007-current)
Coordinator of Cluster Course Program (2006-current)
Member of Business Division’s Individual Studies Committee (2004-current)
Member of 5 Campus Search Committees (Spring 2005, Summer 2005, Spring 2007 (2), Spring 2008)
Member of General Education Committee’s Subcommittee on Assessment (2003-2004)
Member of Campus Pride Committee (2003-2004)
Organizer of Faculty-Staff Intramural Basketball Team (Fall 2004, Fall 2005; Fall 2006; Fall 2007)
* Updated September 2008