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Essays on Institutions and Innovation

by

Deepak Hegde

A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctor of Philosophy
in
Business Administration
in the
Graduate Division
of the
University of California, Berkeley

Committee in charge:

Professor David C. Mowery, Chair

Professor Bronwyn H. Hall
Professor Steven Tadelis
Professor Catherine Wolfram
Professor Brian D. Wright

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Essays on Institutions and Innovation

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by

Deepak Hegde

Abstract

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Doctor of Philosophy in Business Administration
University of California, Berkeley

Professor David C. Mowery, Chair

The three chapters of this dissertation analyze the influence of three fundamental institutions – markets, law, and politics – on the generation and commercialization of new ideas (innovation). The analyses are empirical, and apply the theoretical perspectives of economics, law, and political science.

The first chapter asks: how do real world managers deal with adverse selection and moral hazard problems in the market for ideas? To answer this question, the chapter analyzes a new sample of 505 of arm's-length contracts, negotiated during the 1995-2008 years, between inventors and developers of biomedical inventions. The statistical findings are consistent with agency theories that propose mitigating the information problems with two-part payments consisting of upfront fees and output-based royalty rates. But I also find that licenses include other types of payments (*viz.* minimum royalty payments and milestone payments) to address the transaction costs of verifying outputs and the uncertainty associated with developing novel inventions.

The second chapter investigates political influence in the allocation of public funds for the generation of ideas. The chapter studies U.S. Congressional appropriations committee bills and documents, and argues that although appropriators do not earmark federal funds for biomedical research performers, they support allocations for those research fields that are most likely to benefit performers in their constituencies. The econometric analysis uses data on peer reviewed grants by the National Institutes of Health during the years 1984-2003, and finds that performers in the states of certain House appropriations committee members receive 5.9–10.3% more research funds as compared to unrepresented institutions. Members appear to support funding for the projects of represented research performers in fields in which they are relatively weak, and counteract the distributive effect of the peer review process.

The third chapter (coauthored with Professors David C. Mowery and Stuart J. H. Graham) exploits the Y1995 change in U.S. patent term to understand the use of continuations by firms in the prosecution of their patents during the years 1981-2000. The findings suggest that biomedical firms use continuations to lengthen the duration of patents protecting their most valuable ideas, while electronics and semiconductor firms use the process to augment the size of their patent portfolios. Firms use different types of continuations – the Continuation Application, the Continuations-In-Part, and Divisions – for different ends. Hence, U.S. patent laws, and their reform, can benefit from a closer consideration of the type of continuation filed by applicants.

Contents

List of Figures	iii
List of Tables	iv
Acknowledgements	v
Introduction	vi
1 Imperfect information and contracts in the market for ideas: evidence from the licensing of biomedical inventions	1
1.1 Introduction	1
1.2 Empirical implications of imperfect information theories	4
1.2.1 Framework & Assumptions	4
1.2.2 Implication of the perfect information benchmark	4
1.2.3 Implications of hidden quality	5
1.2.4 Implications of unobservable effort	6
1.3 The Sample	7
1.3.1 Sample description	7
1.3.2 Sample selection issues	9
1.4 Variables and descriptive results	9
1.4.1 Contractual payment terms	9
1.4.2 Measuring symmetrically known quality, hidden quality, and private information	10
1.4.3 Measuring unobservable effort	12
1.4.4 Control variables	14
1.5 Results and robustness checks	15
1.5.1 Estimation and issues	15
1.5.2 Results for upfront fees and royalty rates	17
1.5.3 Results for minimum royalty payments and milestone payments	18
1.5.4 Robustness checks	19
1.6 Concluding remarks	20
2 Political influence behind the veil of peer review: an analysis of public biomedical research funding in the U.S.	36
2.1 Introduction	36
2.2 An overview of the Congressional appropriations process for biomedical research	38
2.2.1 The National Institutes of Health and biomedical research	38
2.2.2 The Congressional appropriations process and the NIH	39
2.2.3 Indirect Political Transfers in NIH Appropriations	40

2.3 Empirical specification and data	43
2.3.1 Empirical specification	43
2.3.2 The data	43
2.4 Results	45
2.4.1 Committee member influence	45
2.4.2 Robustness checks and alternative explanations	46
2.4.3 Additional results	48
2.5 Political influence and the concentration of federal research funds	48
2.6 Concluding remarks	50
3 Pioneering inventors or thicket-builders: which U.S. firms use continuations in patenting?	62
3.1 Introduction	62
3.2 Continuations: definitions and use.....	64
3.2.1 The patent prosecution process and continuations	64
3.2.2 Types of continuing applications	65
3.2.3 Continuations, patent characteristics, and applicant characteristics	65
3.3 Methodology and data	68
3.3.1 Continuations use in different technology classes	69
3.3.2 Continuations and technological “value”	69
3.4 The empirical specification	70
3.3.1 Independent variables: Patent and firm characteristics	71
3.5 Results	72
3.6 The effects of the 1995 change in patent term on continuations behavior	74
3.7 Concluding remarks	75
Conclusion	83

List of Figures

1.1 Box plot of Sample Royalty Rates by License Type	22
2.1 Total NIH Extramural Grants	52
2.2 NIH Extramural Grants by Performer Type	53
3.1 Continuations by Patent Technology Class	78
3.2 Trends in Continuations Types	79

List of Tables

1.1 Agency Theory Predictions about Contractual Upfront fees & Royalty Rates	23
1.2 Therapeutic Categories of Sample Licenses	24
1.3 Organizational Forms of Sample Inventors & Developers	26
1.4 Assignee Types of In-Sample & Out of-Sample Patents	27
1.5 Sample Summary of Payment Terms	28
1.6 Sample Summary of Explanatory and Control Variables	29
1.7 Regression Estimates of Effects of Hidden Quality & Unobservable Effort Proxies on Upfront Fees & Royalty Rates.....	30
1.8 MLE (Tobit) Estimates of Effects of Hidden Quality & Unobservable Effort Proxies on Minimum Royalty & Milestone Payments	32
1.9 Regression Estimates of Effects of Hidden Quality & Unobservable Effort Proxies on Contractual Payments	34
2.1 Institutes & Centers at the National Institutes of Health	54
2.2 Number of Appropriations Committee Members by Chamber	55
2.3 States Represented in the House (A) & Senate (B) LHHE Subcommittee	55-6
2.4 Least Squares Regression Estimates of Returns to House & Senate Committee Representation	57
2.5 Estimates of House & Senate Committee Representation Effects	58
2.6 Pooled Least Squares Estimates of Returns to House Committee Representation on Entry & Exit of Members	59
2.7 Pooled Least Squares Estimates of Returns to Committee Representation by Research Performer Type	60
2.8 Returns to House Committee Representation by Quality of Research Field	61
3.1 Technological “Value” of Continued Patents by Technology Class	80
3.2 Descriptive Statistics for Compustat Firms.....	80
3.3 Multinomial Logit Estimates of Continuations Decisions	81
3.4 The 1995-Policy Change & MLNM Estimates of Continuations Choices	82

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Introduction

New ideas, or innovations, drive modern businesses and economies. The value of new ideas however is known by a few, typically its inventors, or revealed only after costly investment in their development. This imperfect information aspect of new ideas poses distinct challenges to their finance, organization, and commercialization. The three chapters of my dissertation analyze the influence of three fundamental institutions – market mechanism, political organization, and legal framework – on these challenges.

The first chapter studies the market for ideas; it asks: how do arm's-length contracts between sellers and buyers of ideas deal with imperfect information problems? The study employs a sample of 505 license contracts between inventors and developers of biomedical inventions to test the predictions of *hidden quality* and *unobservable effort* theories about contractual payment schemes. The analysis reveals: (a) royalty rates provide incentives for the transfer of inventors' "tacit knowledge" or unobservable inventor effort (b) upfront fees address the transfer of inventors' "codified know-how" or observable inventor effort, as well as unobservable developer effort (c) minimum royalty payments are used by informed inventors to signal their inventions' hidden quality, and (d) milestone payments are related to uncertainties in the development of valuable early-stage inventions. Firms use a variety of contractual provisions to cope with the information challenges inherent in the exchange of new ideas.

The second chapter probes political influence in the allocation of public funds for the generation of ideas. This investigation draws on U.S. Congressional appropriations committee documents and shows that although appropriators do not earmark federal funds for biomedical research performers, they support allocations for those research fields that are most likely to benefit performers in their constituencies. Such disguised transfers mitigate the reputational penalties to appropriators of interfering with a merit-driven system. The statistical tests use data on all peer reviewed grants by the National Institutes of Health during the years 1984 – 2003, and find that performers in the states of certain House appropriations committee members receive 5.9 – 10.3 percent more research funds as compared to unrepresented institutions. The returns to representation are concentrated in state universities and small businesses. Members support funding for the projects of represented research performers in fields in which they are relatively weak, and counteract the distributive effect of the peer review process.

The third chapter (coauthored with David C. Mowery and Stuart J. H. Graham) analyzes the use of "continuations" – a procedure intended by the U.S. patent law to strengthen the intellectual property rights of inventors of pioneering ideas. The chapter employs novel data on applicants and their filings of three types of continuations – the Continuation Application (CAP), the Continuations-In-Part (CIP), and Divisions – during the years 1981-2000 to distinguish among the motives for continuing patents. The statistical analysis finds that CIPs are disproportionately filed by R&D-intensive firms that patent heavily, and that these continuations are more common in chemical and biological technologies. Patents issuing from CIPs cover relatively important inventions and their use appears consistent with a

strategy of protecting “pioneering inventions.” In contrast, CAPs and Divisions are associated with less important patents assigned to capital-intensive firms, particularly in computer and semiconductor fields, and appear to be used in defensive patenting strategies. The study also analyzes the effects of the 1995 change in patent term, and finds that the change reduced continuations overall and shifted the output of continuations towards less important patents.

The three essays of my dissertation, I hope, are starting points of an agenda that seeks to understand the complex interplay among institutions, the innovation process, and economic performance. The dissertation concludes by outlining the next steps for this agenda.

Chapter 1

Imperfect information and contracts in the market for ideas: evidence from the licensing of biomedical inventions

1.1 Introduction

The market for ideas is characterized by imperfect information. The inventors of a new idea and those who seek to develop it may have different expectations regarding the idea's quality; yet credible demonstration of quality risks the idea's expropriation by potential buyers (Arrow 1962).¹ This *hidden quality* problem poses difficulties for the two parties to agree upfront on a price for the idea. Even if they agree on a price, the parties may differ in their incentives to invest *unobservable effort* required to develop the idea. "Arm's-length" trades in the market for ideas hence are hard to achieve, and numerous theoretical studies consider the design of optimal contracts to mitigate imperfect information problems.²

Agency theory recommends mitigating the problems – adverse selection (hidden quality) and moral hazard (unobservable effort) – with two-part payment schemes consisting of upfront fees and revenue-based royalty rates.³ According to *adverse selection* models, the informed party uses the two parts as signaling devices to convince the uninformed party about the *hidden quality* of its inputs (e.g. Lazear 1986, Gallini & Wright 1990). Thus, privately informed inventors signal their ideas' superior quality by offering contracts with high royalty rates and low upfront fees to developers,⁴ while privately informed developers compensate superior ideas with high upfront fees and low royalty rates. According to *moral hazard* models, two-part payments provide the parties with appropriate incentives to invest *unobservable effort* in developing the idea (e.g. Holmström 1979, Jensen & Thursby 2001). Thus, when developers require inventors' unobservable effort in development activities, the optimal contract favors

¹ In this study's setting, patents allow the inventor to reveal the idea, but not the idea's quality, without the fear of expropriation. Accordingly, I focus on the hidden quality problem, not the inventors' expropriation concerns here. Anton and Yao (1994) theoretically investigate the latter problem.

² Kamien (1992) surveys relevant theory. Recent theoretical studies on the topic are: Arora (1995), Macho-Stadler *et al* (1996), Jensen & Thursby (2001), Crama *et al* (2008), and DeChenaux *et al* (2009).

³ The terms "hidden quality" and "unobservable effort" are respectively synonymous to "hidden information" and "hidden actions" conventionally used in the agency theory literature.

⁴ The intuition is that because royalty rates are expressed as a percentage of revenues and revenues reveal the true quality of an idea, an inventor informed of her ideas' superior quality separates herself from inferior inventors by accepting royalty rate payments instead of upfront fees. Uninformed developers commit to such contracts since royalty payments to the inventor will be low if the idea turns out to be bad.

higher royalty rates, while inventors concerned about unobservable developer effort prefer higher upfront payments.⁵

The prescriptions of theory notwithstanding, we do not yet know how real world contracts between inventors and developers of new ideas deal with the information hazards. One obstacle has been the lack of contract-level data. The goal of this study thus is to gather a large sample of contracts between inventors and developers, and test whether the contractual payment schemes are consistent with the predictions of two-sided hidden quality and unobservable effort theories. For this purpose, I assemble and exploit a sample of 505 licenses between inventors and developers of biomedical inventions negotiated during the years 1995-2008. The license contracts were reported as “material” by public corporations in their U.S. Securities and Exchange Commission (SEC) filings, and represent high value transactions (the sample mean upfront payment to inventors is \$1.5 Million). I construct contract-level proxies for the private information of inventors and developers, the hidden quality of inventions revealed after the agreement, and the two parties’ unobservable effort, and link the proxies to cross-sectional variation in contractual payment terms. Although theory focuses on upfront fees and royalty rates as primary payment terms, my analysis also examines the minimum royalty payments and milestone payments found in licenses for biomedical inventions.

Inventor-developer contracts in the biomedical industry provide an ideal setting to assess imperfect information theories for the following reasons: (i) the development process for new drugs and devices is expensive, lengthy, and uncertain (the mean drug development process costs \$ 350 Million, takes 7.5 years, and has a success probability of 18%),^{6,7} (ii) since inventors of drugs and devices often lack downstream capabilities, they license out their inventions to specialist developers for testing, manufacturing, and marketing (51% of the drugs launched during 1981-2008 were associated with at least one license agreement);⁸ (iii) the uncertain value of inventions at license date and the division of labor between inventors and developers can lead to divergent assessments of the inventions’ quality and adverse selection; (iv) the commercial success of inventions depends critically on the parties’ application of hard-to-observe “tacit knowledge” in post-agreement development, raising the potential for moral hazard (70% of licensed biomedical inventions require significant “redesign and development” after agreement date)⁹; and (v) patents are known to protect inventors’ intellectual property in the biomedical industry effectively and facilitate the contracting of ideas (Cohen *et al* 2000). These features of the biomedical industry generate a real world context that closely resembles the setting of imperfect information theories.

⁵ This is because royalty rates tie the inventor’s income to revenues that increase with inventor effort.

⁶ Drug “development” refers to the activities between the filing of an “Investigational New Drug” application filed before the start of Phase-1 clinical trials and the approval of a “New Drug Application” by the U.S. FDA. NDA approval signifies readiness for marketing. Most medical devices and instruments are exempt from clinical trials but require either a premarket notification (510K) or premarket approval from the FDA.

⁷ These mean statistics are representative of drugs and not medical devices. The statistics also mask significant therapy-class level variation in development costs, times and success probabilities (see DiMasi *et al* 2003).

⁸ This estimate is from Pharmaprojects, a leading drug-development database.

⁹ According to a survey of biomedical licensors and licensees by the Licensing Executive Society (2008).

My statistical analysis finds that unobservable inventor effort is significantly correlated with higher royalty rates, and unobservable developer effort with higher upfront payments. These *ceteris paribus* results are consistent with two-sided moral hazard models that predict revenue-sharing to address the contracting parties' unobservable effort concerns. Next, contracts between inventors informed of the value of their high quality inventions and developers specify higher minimum royalty payments – a finding broadly consistent with the prediction of inventor adverse selection models. Minimum royalty payments are *contingent* on inventions' successful commercialization, but unlike revenue-based royalty rate payments, do not incur the costs of verifying developers' revenues. Finally, inventions' quality *hidden to both parties* at agreement date is positively related to milestone payments, suggesting that such payments deal with uncertainty about the viability of early-stage inventions. Overall, licenses for biomedical inventions include provisions to address the hazards posed by: the unobservable efforts of inventors and developers, inventors' private information about hidden quality, and uncertainty associated with the development of novel inventions. The provisions are broadly consistent with the prescriptions of agency theory, but their variety also suggests a need for further modeling and empirical research.

This study contributes to the two literatures on contracts and the market for ideas. Previous large sample analyses of contracts under imperfect information have focused almost exclusively on financial contracting, business franchising, and sharecropping arrangements.¹⁰ This prior work has confronted, with limited success, the issues of unobservable revenues and endogenous measures of hidden quality and effort in a setting where imperfect information about product quality is a secondary concern at best. My study uses novel proxies for unobservable revenues, quality, and effort to remedy the limitations of prior studies and presents a unified analysis of two-sided hidden quality and unobservable effort in the ideas market where the hazards are salient. My analysis also focuses on high-value transactions among sophisticated parties likely to adopt contractual safeguards to mitigate the information hazards. The findings hence suggest contractual “best practices” for inventors and developers, particularly start-up entrepreneurs, who lack alternative means such as reputation and complementary assets to mitigate the hazards. The insights from this study can be extended to a variety of contexts where parties trade ideas under imperfect information; for example, in the book publishing, movie production, and consulting industries.

Section 1.2 reviews information theories and their empirical implications for the structure of contractual payment schemes. Section 1.3 describes the study sample and sampling issues. Section 1.4 describes revenue-sharing terms, proxies for imperfect information, and control variables. Section 1.5 discusses regression specifications, limitations of my identification strategy, and results. Section 1.6 concludes with a discussion of findings and avenues for future research.

¹⁰ Hart (2001) surveys agency explanations for the structure of financial contracts. Martin (1988), Lafontaine (1993), and Brickley (2002) are examples from franchising, and Laffont & Matoussi (1995) recently analyze sharecropping contracts.

1.2 Empirical implications of imperfect information theories

1.2.1 Framework and assumptions

Consider an inventor of a new drug or medical device. The inventor has monopoly power over her invention through patent protection but lacks the downstream capabilities to test, manufacture, or market the invention. The inventor has three options to profit from her invention – acquire the downstream capabilities, enter into an alliance with another firm to jointly develop the invention, or license the invention to a downstream firm.

The theoretical models tested here examine contractual payment terms, contingent on the inventor's decision to license. A “license” is an arm's-length contractual arrangement between two legally independent business entities whereby the licensee (the party that commercializes the invention, referred to as “developer” throughout the paper) pays the licensor (the “inventor”) for the right to “use, make and sell” the latter's invention.¹¹ The theoretical models all share the following assumptions.

- A1: The inventor has a comparative disadvantage in commercializing the invention relative to the developer and the parties do not compete in downstream markets.
- A2: Inventor and developers do not engage in repeat transactions for the same invention and do not establish reputations.¹²
- A3: Inventor and developer are risk-neutral.
- A4: Licenses specify two types of payments to the inventor – a lump-sum fee (f) paid upfront only once for the duration of the contract, and royalty payments specified as a percentage of the product's revenues called royalty rate (r).

A common implication of the models is that f and r are negatively related when revenues are held constant (*i.e.* f is the net present value of future payments given the amount of royalties paid to the inventor).

1.2.2 Implication of the perfect information benchmark

Kamien and Tauman (1986) provide a perfect information “benchmark” against which to assess the effects of information imperfections on payment schemes. Their model assumes

¹¹ License contracts represent arm's-length transactions because the parties remain independent entities during the contract term. The inventor transfers the right to use her intellectual property to the developer, who independently makes downstream financing, development, production, and marketing decisions. More complex alternatives for dealing with imperfect information include the sharing of ownership rights as in alliances or joint ventures (Aghion & Tirole 1994). Lerner & Merges (1998) analyze the allocation of control rights in biomedical R&D alliances, and Gans, Hsu & Stern (2001) analyze the effect of transaction costs, control of intellectual property, and sunk costs of entry into product markets on startups' choice of organizational form (*i.e.* alliances, licensing, & acquisitions v/s vertical integration).

¹² Reputation can mitigate the adverse selection and moral hazard consequences of opportunistic behavior. However, even if inventors do not deliberately overstate their invention's value for reputation's sake, they have a documented tendency to be overly optimistic about their inventions' value (Camerer & Lovo 1999). Recent studies also suggest that reputation (*i.e.* a history of repeat transactions between two parties), does not substitute for formal contractual arrangements (Ryall & Sampson 2009).

that both inventor and developer are perfectly informed about the invention's *quality*.¹³ With perfectly informed parties and no inventor effort post-license, an upfront fee license (*i.e.* $r = 0$) is optimal because: (a) a fixed upfront payment, unlike a running royalty, does not increase the marginal costs of downstream development and provides first-best incentives for developer effort, and (b) inventors may find it costly to verify final revenues on which royalty payments are based. Further, with a competitive market for licenses, the inventor charges an upfront fee that fully extracts the invention's value from the developer. Hence, with risk-neutral parties, perfect (symmetric) information predicts a license with $r=0$ and f directly proportional to the invention's quality.

H0: *When all other variables are held constant and with perfectly informed parties, the upfront fee is increasing in the invention's quality.*

1.2.3 Implications of hidden quality

The quality of most biomedical inventions, in an expected value sense, is not perfectly known by both parties at license date. Uncertainty about quality stems from factors such as: vagaries in the technical and commercial feasibility of inventions, delays in testing and regulatory approval of new drugs, challenges in manufacturing and marketing new products, and the threat of entry by competitors. Inventors and developers often differ in their knowledge of these factors, leading them to divergent assessments of an invention's quality. Whether the inventor or the developer is better informed of this "hidden" quality determines the identity of the adversely selected party.

Gallini & Wright (1990) model inventors with private information about their inventions' quality. Experienced inventors may be privately informed about the technical quality of their inventions and have an incentive to overstate quality to extract higher payments from developers. Potential developers, wary of adversely selected inventors, may be unwilling to license in inventions without credible assurances of their quality. In this situation, an inventor of a high-quality invention can separate herself from an inferior inventor by offering a contract with lower upfront fees and higher royalty rates, thereby making her payments contingent on the invention's technical success.^{14,15} Under a royalty scheme, the developer knows that inventor payments will be small if the invention's true quality is low, and commits to the license. Hence, royalty rates serve as a credible signaling device for inventors with high quality inventions.

¹³ I use "quality" to mean expected value (revenues) throughout the paper.

¹⁴ In Gallini & Wright (1990), both low-quality and high-quality inventions are profitable to the developer, but high-quality inventions are more profitable. Since royalty rates distort downstream output, the low-type inventor finds payments from royalties less lucrative than fixed payments. In the separating equilibrium, low-type inventors extract the full value of their inventions from developers (because markets for licenses are assumed to be competitive), and high-quality inventors leave some "information rents" to the developer.

¹⁵ Lazear (1986) is similar to Gallini & Wright (1990) in spirit. The former predicts the use of performance-contingent employment contracts to address asymmetric information about employee type. The idea that informed principals signal their quality with revenue-sharing offers has been empirically investigated in various settings including entrepreneurial finance (Leland & Pyle 1977) and franchising (Lafontaine 1993).

H1a: When all other variables are held constant and with privately informed inventors, the royalty rate is increasing (and the upfront fee decreasing) in the invention's hidden quality.

In many cases, developers with extensive expertise in commercializing inventions are better informed than inventors about the commercial prospects (which affects expected value or quality) of new ideas. Beggs (1992) models privately informed developers and predicts that informed developers confident about the invention's superior quality prefer contracts that pay inventors high upfront fees and low r .¹⁶ Equivalently, informed developers offer contracts with high r (and low f) when they expect the invention to be of inferior quality.

H1b: When all other variables are held constant and with privately informed developers, the royalty rate is decreasing (and the upfront fee increasing) in the invention's hidden quality.

1.2.4 Implications of unobservable effort

The commercial value of biomedical inventions depends crucially on the efforts of both parties in testing, redesign, and development activities undertaken after the license date.¹⁷ Absent appropriate incentives, each party may opportunistically shirk when its efforts are hard to monitor and verify by the other party. In Jensen & Thursby's (2001) model, university-based inventors prefer to focus their efforts on research rather than commercialization, and shirk in commercialization activities because their efforts are not perfectly observed by the developer (even if observable, inventor effort can be costly to monitor and verify by a third party). An upfront fee provides no incentives for the inventors to invest effort in post-license development activities. Royalty payments solve this inventor moral hazard problem by tying the inventor's income to the invention's commercial performance (which increases with inventor effort). This insight also applies to the actions and incentives of nonacademic inventors.

H2a: When all other variables are held constant, the royalty rate is increasing (and the fixed fee decreasing) in unobservable inventor effort.

Similarly, an increase in developers' share in residual profits, revealed by a lower royalty rate, augments developer incentives to invest effort in commercialization.¹⁸

H2b: When all other variables are held constant, the royalty rate is decreasing (and the fixed fee increasing) in unobservable developer effort.

Table 1.1 summarizes the predictions of the above information models about f and r . The empirical implications of adverse selection and moral hazard models are observationally equivalent, underscoring the importance of controlling for one while estimating the effect of

¹⁶ In Gallini & Wright (1990) privately informed inventors have the bargaining power and makes revenue-sharing offers, whereas in Beggs (1992), informed developers make contract offers.

¹⁷ 85% of the sample pharmaceutical inventions were in preclinical stage at the time of licensing. Jensen & Thursby (2001) also report that more than 70% of university licenses require significant inventor and developer effort before commercialization based on a survey of 62 U.S. universities and 112 licensees.

¹⁸ Many developers may license in inventions solely to preclude other competitors from acquiring the technology. In such cases of extreme developer opportunism, inventors should prefer fixed fee licenses.

the other – a point missed by previous piecemeal tests of the information hazards.¹⁹ Three more points are important to note before empirically testing the predictions.

- The predictions of these theoretical models are not mutually exclusive – the terms in real world licenses reflect hidden quality and unobservable effort concerns of both parties, as well as the licensed invention’s quality that both parties are informed of, and agree over. The primary challenge for econometrically identifying the partial effects of the various information-related variables is to construct proxies that capture the effects without biases.
- The models assume a two-part tariff structure with r and f . However, 57% of my sample licenses stipulate other payment terms (either milestone payments or minimum royalty payments). Since recent theory (DeChenaux *et al* 2009) suggests that these terms are substitutes for royalty rates, I also investigate the relationships among milestone fees, minimum royalty payments, and imperfect information.
- The tests below focus on the effects of hidden quality and unobservable effort, and do not address alternative explanations for revenue-sharing such as the parties’ risk preferences and capital constraints. The empirical analyses control for these other factors, however, and where appropriate, discuss their influence on contractual payments.

The next section describes the study sample, measures of symmetrically known and hidden quality, inventor and developer private information, unobservable effort, and control variables. I describe the sample contracts in some detail because the structure of biomedical licenses is not well documented in the literature and the descriptive results can be compared with the structure of licenses either assumed or predicted by other studies.

1.3 The sample

1.3.1 Sample description

The sample license contracts are drawn from the Securities and Exchange Commission (SEC) EDGAR filings of U.S. publicly listed firms during the years 1995-2008. Public companies are required to disclose a variety of “material” transactions in the filings such as: license agreements, franchise agreements, supply and distribution agreements, assignment agreements, and end-user agreements.²⁰ After carefully perusing each individual agreement, I retained arm’s-length license agreements, and eliminated redacted agreements, agreements among dependent entities or those involving the transfer of control rights, and agreements observably tied to other transactions between the parties. I was thus left with 505 complete

¹⁹ Hagerty and Siegel (1988) draw attention to this observational equivalence.

²⁰ A “material” event is any significant event that affects the company’s financial standing such as a bankruptcy, a lawsuit, a merger, employment of key personnel, joint-venture, or a license agreement. Descriptions of material events are reported as amendments in Form 8-K, 10-K or 10-Q reports. Public companies can be exempt from filing the standard SEC forms if they have less than 500 stockholders and less than \$10 million in total assets.

licenses for inventions in the pharmaceuticals, biotechnology, medical instruments and devices industries.²¹ Accordingly, the sampling frame for this study is “material” license contracts covering inventions in the biomedical industry.

I used the descriptions of licensed inventions in the 505 sample contracts to match each invention to one of 65 therapeutic categories and four broad sectors. Table 1.2 shows that 48.3% of the sample biomedical licenses are for pharmaceutical inventions and 44% for medical devices and instruments. The remaining licenses are for genetic (5.5%) and veterinary products (1.8%). Anticancer drugs (general and immunological, with estimated market sizes of \$1-5B per year), Catheters, needles and syringes (market size estimates for this product class are not available), and Cardiovascular devices (estimated market sizes of > \$10B per year) are the three most common therapeutic categories. These therapeutic categories were developed by Pharmaprojects (for pharmaceuticals) and the Medical and Healthcare Marketplace Guide (for medical devices and instruments) to assess the revenue potential of new inventions based on the size of their product markets.²² Industry experts use the categories as a starting point to evaluate the expected value of inventions in licensing negotiations (P.C. with Greg Wiener, 07.06.2009), and I use category specific dummy variables in regressions to control for therapy-level heterogeneity in the expected revenue of inventions. The controls permit estimation of within therapeutic-category effects of imperfect information on contractual payments.

For each license, I collected data on the effective start date, duration, identity of the parties, United States Patent and Trademark Office (USPTO) identifiers for the 1,265 unique licensed patents (both patent applications and issued patents), revenue-sharing terms (upfront payments, royalty rates, milestone payments, and minimum royalty fees), and other terms (field of use exclusivity and territory of use). For each licensed patent, I gathered its issue date, number of citations in every year after its issue (through 2008), number of references to previous patents and scientific literature, and USPTO class and subclasses.²³

The sample contracts were reported by public companies in their role as either inventors (licensors) or developers (licensees). Table 1.3 shows the sample distribution of U.S. for-profit corporations, universities, individuals, and foreign entities as inventors and developers. U.S. corporations are inventors in 47% and developers in 87% of the transactions. U.S. universities (22%) and individuals (10.5%) are other major sources of inventions.²⁴ The low frequency of universities, non-profits and individuals among developers reflects the widely held view, consistent with assumption *A1*, that these organizational forms are comparatively disadvantaged relative to corporations in downstream development.

²¹ “Biomedical” as used here includes the following SIC-2 categories: 28 - Chemicals & allied products; 38 - Measuring, Analyzing, & Controlling Instruments, Medical And Optical Goods; 50 - Wholesale Trade - Durable Goods; 80 - Health Services; 87 -Engineering, Accounting, Research, Management, & Related Services.

²² Pharmaprojects is the pharmaceutical industry’s leading drug development database. “Medical and Healthcare Marketplace Guide” is an annual industry publication that focuses on medical instruments and devices. I confirmed these matchings by using the services of a graduate pharmacology student.

²³ USPTO patent subclasses are finer categorizations than therapeutic categories – a patent in a given therapeutic category can fall into any one of the more finely defined 2-8 USPTO subclasses.

²⁴ This distribution is comparable to the distribution of organizational types reported by others (licensing executives survey 2008, Taylor & Silberston 1973, Caves *et al* 1983, Anand & Khanna 2001).

1.3.2 Sample selection issues

The sample licenses are not randomly drawn but the selective disclosures of U.S. public corporations, which arguably are more expert (than unlisted entities) at evaluating inventions and writing sophisticated contracts. Hence, the primary effect of this selection is to generate a closer match between the sample parties and the value-maximizing actors assumed by theory. Still, to get a better sense of selection of inventors into the sample, I compared the inventors (assignees) of the 1,265 US patents associated with the 505 sample licenses to the inventors of the 170,955 US patents not in the sample but in the same USPTO subclasses as the licensed patents. The two subsamples together represent the population of all U.S. inventions patented during the years 1976-2008 in the technology fields of the sample patents.

Panel-A of Table 1.4 shows that U.S. universities and the federal government are disproportionately represented as inventors in the sample. Since universities and federal laboratories rarely engage in development, this difference is consistent with assumption *A1* that inventors are not active in downstream markets. Thus, it does not appear plausible that these artifacts of sample-selection will bias inferences from the sample of the effects of imperfect information on contract terms. Nevertheless, dummy variables for inventor and developer organizations in the following estimations pick up potentially unobserved differences among the different organizational types.

A second source of potential bias arises from the quality of sample inventions, since only transactions valuable enough to meet the materiality requirements for disclosure by public companies are represented in the sample.²⁵ Panel-B of Table 1.4 presents summary statistics for the citations (a proxy for quality) of in-sample patents and matched “out of sample” patents at and after agreement date.²⁶ The average licensed patent has 40% more citations at agreement date relative to the average out-of sample matched patent and twice the number of citations as matched patents after license date. It is not clear whether these differences in citation patterns reflect differences between the population of licensed patents and patents that are not licensed, or between in-sample and out of sample patents. In either case, this oversampling of valuable inventions reinforces the likelihood that the sample contracts are the result of careful negotiations between value-maximizing parties, and resemble the contracts prescribed by theory.

1.4 Variables and descriptive results

1.4.1 Contractual payment terms

Contractual payment terms – royalty rates, upfront fees, milestone fees and minimum royalty payments – are the dependent variables of this study. Royalty rate (r), expressed as a

²⁵ Firms sometimes redact key contractual terms (like payments, license dates and patent numbers) from their SEC filings and redacted licenses are omitted from my sample. If firms redact licenses with strategically important or valuable inventions, then it is plausible that my sample licenses are biased towards less-important inventions.

²⁶ The matching was done on the basis of USPTO patent subclass and grant date.

percentage of gross sales revenues to be paid to the inventors on an annual basis, is required by all the 505 sample licenses.²⁷ 73% of the licenses stipulate upfront fees (f).

Apart from f and r , 40% of the sample licenses specify a lower bound on annual royalties. These minimum payments are *contingent on commercialization*, credited against annual royalty rate payments, and continue through the expiration of the agreement. I calculate minimum royalty payments (p) as the net present value of annual minimum payments (discounted at 5% *p.a.*) over the term of the agreement.

27% of the licenses also specify milestone or *state-contingent* lump-sum payments. Typical milestones are: the filing of an “investigational new drug” application by the licensee, completion of successive phases of clinical trials, regulatory approval of “new drug applications,” and first commercial sale of the final device or drug. These payments are most common in pharmaceutical industry licenses, where the development phase is lengthy and comprises of the different states. Milestone payments (m) are the sum total of all state-contingent payments to the inventor.²⁸

Table 1.5 presents summary statistics for the four payment types. Statistics for f , m and p are calculated for non-zero values, and expressed in FY2008 constant dollars. The median r (5%) approximates the mean (5.5%), but the other three payments exhibit substantial variance and skew. The mean f of \$1.5 Million is well above the median (\$ 214,000). When present, minimum and milestone payments are economically significant (\$1.6 M and \$ 4 M respectively), and on average, exceed upfront fees. These statistics should be interpreted cautiously – over 80% of biomedical inventions fail during testing and many of the payments (milestone payments and royalties) do not materialize.²⁹ Thus the numbers represent potential payments, not actual transfers.³⁰

1.4.2 Measuring symmetrically known quality, hidden quality, and private information

Theory predicts that contractual payment terms are affected by the parties’ commonly-held and private information about the invention’s expected value. In an ideal world, the effect of information can be measured with data on expectations about quality that the parties agree on, the extent of private information about the invention’s hidden quality, and the identity of the informed party at agreement date. Since these data are practically impossible to observe, I use indirect measures for the level of the invention’s symmetrically known quality, its

²⁷ This is consistent with the findings of Taylor & Sylberston (1973), Contractor (1981), and Anand & Khanna (2001) all of who report a less than 10% incidence of zero-royalty licenses.

²⁸ Since the exact dates for the realization of milestones are not available, I do not report discounted NPVs but just net milestone payments here.

²⁹ The probability of eventual FDA approval ranges between 8% and 37% (depending on therapeutic categories) for New Chemical Entities that enter the clinical testing stage (Adams & Branter 2006; DiMasi *et al* 2003)

³⁰ 9 of the licenses in my sample (all with university licensors) required the developer to sponsor inventors’ research. However, these sponsorships were either specified as state-contingent payments or deferred upfront payments and accordingly I treat them as milestone and minimum payments respectively. The results reported here are not sensitive to either the exclusion of these payments or the exclusion of contracts with these payments.

hidden quality, and the private information available to the inventor and the developer at agreement date.

First, I construct measures for the symmetrically known and hidden components of the invention's quality (expected revenues) based on the number of citations received by licensed patents. My assumption, that the number of citations captures a patent's quality, is based on the following findings.

- Trajtenberg (1989) found a strong positive correlation between the commercial value of different scanners within the Computed Tomography field (measured by sales revenues from hospital purchases of CT scanners) and the citations received by patents associated with the scanners.
- Harhoff *et al* (1999) surveyed German patentholders of U.S. patents and asked them to evaluate the selling price of their patents three years from the survey date. The responses were linked with the citations received by the patents three years after survey date. Each additional citation to the sample patents was worth an increased valuation of \$1 million.
- Hall *et al* (2005) report a direct relationship between the citation stocks of U.S. firms' patents and the market value of these firms measured by Tobin's-q. Firms with patents that are cited 20 times or more commanded a "market-premium" of up to 54%.
- Of direct relevance to the proxies used here, real-world licensing executives use citations to assess the quality of patented inventions and the value of licensing transactions (see Ocean Tomo, a leading IP aggregator's 2008 catalogue, or Parr 2002).

I observe the citations of licensed patents at a date after the agreement date. This retrospective view allows me to decompose the citations into two parts: citations that arrived *before* agreement date, and citations that arrived *after* agreement date (but before 2008, the last year for which I have citations data). The first part proxies for the invention's *symmetrically known quality*, and the second part reveals the invention's *hidden quality* at agreement date as explained below.

Symmetric information about inventions' quality

The number of citations to licensed patents *before* the agreement date is directly correlated with symmetric information about the invention's quality at license date, since both inventor and developer observe the citations. Citations at agreement date thus capture information relevant to the invention's expected revenues known by both parties, and serves as a proxy for the symmetrically known expected value of the invention.

Hidden information about inventions' quality

Citations to licensed patents that arrive *after* agreement date have information on the invention's hidden quality once we remove future citations that are predicted by the citation

history at agreement date (since past citations are a good predictor of future citations). The “purging” is easily accomplished by disaggregating post-agreement citations into a predictable component based on the citations at agreement date and a residual component. When both pre-agreement and post-agreement citations are included on the Right Hand Side (RHS) in a multivariate regression, the coefficient on the post-agreement citations variable captures the effect of this residual component. The residual proxies for the “unexpected” or hidden quality of the licensed invention at agreement date.

These citation-based proxies require refinement because: (a) patents in different technologies and therapeutic categories have different citation patterns; (b) patents (both within and across licenses) issued in different years have different durations of time during which they can be cited by other patents; and (c) a typical license is associated with multiple patents (the median agreement in my sample licenses 2 patents). To correct for these sources of noise, I first normalize the citations of each licensed patent at any given date by dividing the citations by the number of citations received by the average patent in the same USPTO technology subclass and vintage as the licensed patent. I then calculate the quality proxies for each license as the mean of the normalized citations of all patents in the license.

Private information about inventions’ quality

Next, I use the number of other patents held by the two parties in the same USPTO patent subclass as the licensed invention at agreement date as proxies for their respective levels of information about the focal invention’s quality. The interaction between the number of other patents held by inventors and developers and the post-agreement citations of patents covering the licensed invention identify the effect of the parties’ private information about the invention’s hidden quality. Since my regressions include fixed effects for the 65 therapeutic categories, the estimated effects of the above proxies capture within product class relationships between information about the inventions’ quality and contractual payments.

Panel A of Table 1.6 reports summary statistics for the number of patents held by inventors and developers as well as the proxies for symmetrically known and hidden information about inventions’ quality. A majority of inventors (61%) and developers (86%) do not have patents in the same field as the licensed invention at agreement date, skewing their summary averages towards zero. The unit value of normalized citations for the median licensed invention at license date suggests that at the time of licensing, the quality of the median licensed invention is not statistically different from an average invention. The median invention after agreement date, however, is 1.5 times more valuable than an average invention of comparable technology and vintage.³¹

1.4.3 Measuring unobservable effort

An ideal test of two-sided moral hazard should relate the importance of the parties’ efforts and the cost of monitoring effort to payment schemes. Because I do not have fine-grained

³¹ The sample median patent is licensed 3 years after its grant. 8 years is the median difference between the time the median patent is licensed, and the date of its last citation (in year 2008).

measures for unobservable effort, I use the presence of inventor and developer effort-related clauses in the licenses to identify moral hazard as follows.

Inventor effort

In its most basic form, a license confers the developer the right to make, use and sell products with the inventor's patents. Many licenses, in addition to the right to infringe upon inventor patents, require the transfer of inventor knowledge to the developer. These knowledge transfers requiring inventor effort are indicated by the presence of two qualitatively distinct clauses.

(i) Know-how clauses specify the transfer of items that are easy to specify, monitor, and verify such as: blueprints, drawings, data, records, prototypes or other material required by the developer to practice the licensed patents. Know-how clauses may sometimes also require the inventor to train developer personnel to use the transferred material. The following contractual language from a sample license illustrates know-how clauses:

"Know-How means all of Licensor's technical know-how and other knowledge, information, plans, drawings, instructions, software and engineering advice relating to any and all of the Licensed Products developed by Licensor that Licensor, in its reasonable determination, believes can be used in the myocardial ablation field;"

Panel B of Table 1.6 reports that 41% of the sample agreements specified a know-how clause.

(ii) Show-how clauses or "inventor assistance" clauses stipulate technical services by the inventor to support the developer's commercialization activities. Show-how clauses require the inventor to assist in development activities that are difficult to accurately specify *ex ante* and verify *ex post* – for example, assistance in: redesign and development, the conduct of clinical trials, seeking regulatory approval and manufacturing activities. The difficulty of verifying the level and quality of assistance is underscored by the use of words like "reasonable" to specify the expected level of assistance. For example:

"The Owner (COLTHURST LIMITED) shall be responsible for reasonably assisting Holmedco in the Development of the Products. Holmedco shall pay Owner for such services at the rate of \$15,000 US per month, such payments to be retroactively paid for services commencing June 1, 1994 through FDA Phase II approval for marketing."

"DynaGen agrees to provide reasonable technical assistance to Licensee to assist Licensee in the development of the Licensed Products. Licensee shall reimburse DynaGen for labor and material costs incurred by DynaGen at Licensee's written request. DynaGen's employees time shall be billed at \$80 per hour for scientists and \$160 per hour for management personnel"

18.6% of the sample agreements specified a show-how clause.

Both know-how and show-how clauses explicitly refer to compensation for the inventor's time separate from the revenue-sharing terms. The key difference between the transfers of know-how and show-how is that the former relates to the transfer of codified or verifiable knowledge, while the latter requires the application of inventors' difficult to verify "tacit knowledge" in development activities. Hence, I use the presence of show-how clauses in licenses as a proxy for the presence of *unobservable* inventor effort and know-how clauses to indicate *observable* inventor-effort. Admittedly, a careful reading of contractual language suggests that the two proxies are not perfect – the quality of at least some of the inventor activities specified in know-how clauses is hard to monitor and most show-how clauses imply sharing of at least some of the inventor's codified know-how in addition to tacit knowledge. Hence, a know-how clause should be interpreted as indicating inventor actions that are more visible to the developer relative to those specified by show-how clauses.

Developer effort

Some developers may license patents exclusively to preclude inventors from licensing their inventions to competing developers. In other cases, developers may consider their share of profits insufficient to go forward with the investments to commercialize the invention (DeChenaux *et al* 2009). "Due-diligence" clauses stipulate a minimum level of developer effort and I use these clauses as a proxy for concerns about developer opportunism and the importance of developers' unobservable effort. For example:

"Licensee shall use commercially reasonable and diligent efforts to develop Licensed Products or Licensed Services and to introduce Licensed Products or Licensed Services into the commercial market. Licensee shall spend at least Two Hundred Thousand Dollars (\$200,000) per year for the first two (2) years and One Hundred Thousand Dollars for the following six (6) months of the term of this Agreement on research and development and other activities directed to the commercialization of the Patent Rights and other University technology related to the cloning of animals."

"HenKan shall use Commercially Reasonable Efforts to develop the Product in each country in the Territory as soon as practicable."

36% of the sample licenses specified a "due-diligence" clause.

1.4.4 Control variables

Identifying the effect of hidden quality and effort on payment terms requires controlling for a variety of factors potentially correlated with payment terms and the explanatory variables. First, I include other terms in contracts (the number of licensed patents, exclusivity, duration, and territory) on the RHS as potential correlates of payment terms.³² Panel C of Table 1.6 shows that 83% of the sample licenses are either exclusive or

³² Agreements are defined to be effective till the expiry of the last licensed patent. I calculated the duration for the sample agreements as the difference between agreement start date and the expiry date of the last patent.

exclusive to field of use (therapeutic category). 87% of licenses grant the developer world-wide rights to the practice of licensed patents. The median license duration (the time between the agreement start date and the day on which the licensed patents expires) is 16 years – a reasonable length of time to recoup developer investments in commercialization for a product that may be introduced to the market until 8-10 years after the agreement date.³³ The median invention in my sample is protected by 2 patents. The sample statistics on exclusivity and duration are consistent with assumption *A2* that inventors do not license out their inventions more than once (either to the same, or to a different, party) precluding invention-specific reputation as a factor affecting payment terms.

Second, while theory assumes risk-neutral parties (*A3*), the relative risk preferences of real world negotiators may be correlated with the use of effort-related payments (risk-averse parties prefer the insurance of fixed payments rather than royalties). I include variables for the length of time the parties have been active in invention (organizations with a longer inventive history may be less risk-averse) and their organizational types (*i.e.* corporations, small firms, individuals, universities, other non-profits, and foreign entities) as first order controls for factors like risk preferences and liquidity constraints.³⁴ Panel D of Table 1.6 shows that inventors' patenting history is on average twice as long as that of developers at license date ("inventive age" is the difference between the application year of the party's first patent in any field and agreement date). I also control for industry-wide trends in the preferences for certain types of revenue-sharing terms or the value of innovations by including a logarithmic trend variable.

Third, characteristics of the invention such as its closeness to basic science may affect commercialization efforts and payments. Previous literature has shown that patents protecting embryonic or early-stage inventions have a higher proportion of references to prior scientific literature (Narin *et al* 1997). Hence, I use the proportion of references to scientific literature in the licensed patents, normalized as described in Section 1.4.2, to capture the developmental stage or maturity of the licensed invention. Inventions' product-class factors like market size, volatility, technological opportunity, availability of substitutes, or the threat of competition can also affect payments, and the 65 therapeutic category dummies control for these factors that vary with product categories. All coefficients can thus be interpreted as within-product class effects.

1.5 Results and robustness checks

1.5.1 Estimation and issues

The statistical tests in this section regress contractual payment terms on proxies for hidden quality and hidden effort with controls for the characteristics of inventions, licenses, inventors and developers explained in the previous section. The cross-sectional nature of the

³³ 17 of my sample agreements compensated the inventor with the developer's equity. Either excluding these contracts or controlling for the provision of equities on the RHS do not alter the findings reported here.

³⁴ The large numbers of unique inventors (401) and unique developers (407) relative to sample size (505) precludes the inclusion of organization-specific dummy variables.

sample and the absence of direct measures for quality and effort pose the following challenges to the identification of imperfect information effects.

First, the proxy for hidden quality may be endogenous to payment terms. Citations to licensed patents after the agreement (proxy for hidden quality) may increase when royalty rates are higher because inventors respond to the potential of higher profits with efforts that increase the invention's quality and the number of citations. Any RHS measure of hidden quality based on post-agreement outcomes that does not control for the parties' efforts is similarly susceptible to this endogeneity problem. However, my regression specifications estimate the effect of the parties' information about quality after partialling out the effect of their efforts. Hence, it is unlikely that the estimated effects of the two-sided hazards on payment terms are biased due to correlations between quality and effort.

Second, contractual payments and the presence of effort-related clauses (know-how and show-how) are simultaneously negotiated. Hence, one can argue that rather than the presence of effort-related clauses determining (f, r) , the payment terms determine the inclusion of the clauses, biasing regression estimates of the effect of effort on (f, r) . The direction of this potential simultaneity bias depends on how equilibrium payments affect the presence of the clauses: if higher royalty rates (and lower f) systematically result in the inclusion of, say, show-how clauses, then the effect of show-clauses (proxy for unobservable effort) on r will be overestimated, but if developers omit show-how clauses as redundant when they specify a higher share of revenues (r) to inventors, then the effect of the clauses on r will be underestimated. Since time-constrained inventors arguably have no incentive to submit to the presence of effort-related clauses without suitable compensation (the presence of these clauses represents obligations that can be costly to inventors), it is unlikely that a higher r (or lower f) results in the inclusion of show-how clauses other than as an incentive for inventor unobservable effort. Hence, the plausible consequence of simultaneously determined contractual payment terms and effort-related clauses is to bias the estimated effects of effort in favor of the null hypothesis.

Third, for two-part payment schemes, theory assumes that upfront fees represent the inventor's share of revenues given the net present value of all future royalty payments. This implies that holding revenues constant, f and r are inversely related (assumptions *A4* & *A5*). Hence, regressions in the reduced form should either estimate the effect of imperfect information proxies on the ratio of upfront fees to the *net present value of royalty payments* over the duration of contracts, or control for the net present value of revenues while estimating the effect of RHS variables on f and r . Omitting revenues from the regressions will yield biased estimates of hidden quality (or effort) on (f, r) if hidden quality (or effort) is correlated with both revenues and revenue-sharing terms. The same argument holds for licenses with m and p – the terms may be substitutes for each other or for (f, r) , and unbiased estimation of the effects of quality and effort on these terms requires controls for expected revenues. Although I do not observe the final revenues associated with licensed inventions, I include 65 therapeutic-category dummies and citations to licensed patents normalized by USPTO

patent subclass and issue date.³⁵ These variables respectively control for across- and within-product-class variation in the expected revenues for licensed inventions.

Fourth, as noted before, not all sample licenses involve the payment of f , p or m . When these payments are absent, the dependent variable in the corresponding estimating equations is bounded below at zero. I handle this censoring problem with maximum likelihood Tobit estimations for f , p and m . I estimate the Tobit equations after converting the three dollar payments to a partially logarithmic scale (*i.e.* $y = \log [1 + \text{payments}]$ where y represents the transformed dependent variable) due to the significant skew and variance in the distribution of these variables.

Fifth, the sample is cross-sectional and I cannot reject the presence of heteroskedasticity of unspecified form. Hence, I calculate and report Huber-White robust standard errors on all coefficients.

The following sections first consider the effect of the RHS variables on f and r and then on m and p .

1.5.2 Results for upfront fees and royalty rates

Table 1.7 summarizes the information-related assumptions of the different theory models, corresponding proxy variables, and predictions about contractual f and r . The last two columns of the Table respectively report MLE (Tobit) estimates of $\log(1+f)$ (where f the upfront fee is in 1000s of Y2008 \$) and OLS estimates of royalty rates (expressed in percentages) on the hidden quality and hidden effort proxies.³⁶ The estimates represent effects of RHS variables with respect to a baseline contract between symmetrically informed parties with no inventor effort in development.

Citations to licensed patents at agreement date are significantly positively associated with f . The presence of know-how clauses, indicating the transfer of codified knowledge, also significantly increases f . Upfront payments are not statistically different for licenses with show-how clauses, which proxy for the transfer of inventor tacit knowledge, and ordinary patent licenses. Due-diligence clauses, indicating safeguards against potential developer opportunism, are associated with a near doubling of f (the magnitudes of the coefficients are gauged from the computed marginal effects of the variables not reported here). Hence, fixed fees are positively related to the symmetrically known quality of the invention at agreement date, the transfer of observable inventor effort, and the potential for developer moral hazard, results that are respectively consistent with $H0$, $H2a$ and $H2b$.

Licenses with show-how clauses are associated with royalty rates that are nearly twice as large as those associated with an average licensed patent. Licenses with know-how clauses are

³⁵ Actual revenues are hard to gather because: (a) 70% of licensed inventions fail to be developed into revenue-yielding products (b) the average time-gap for pharma inventions between agreement date and first product sales is 4-10 years (Pharmaprojects 2009, Adams & Branter 2006), and (c) firms rarely disclose product level revenues.

³⁶ I also estimated the royalty rate equation using a logistic transformation that maps the rates (divided by 100) to the real line ($z = \ln[r/(1-r)]$) where z is the transformed variable). The results reported are robust to this transformation.

also associated with higher r than ordinary licenses, but their effect is not as large as that of show-how clauses. This result suggests that the presence of a “know-how” clause may not be a perfect proxy for observable effort, perhaps because the transfers of materials, data and training of developer personnel stipulated by this clause involves inventor actions that are hard to monitor and compensate with upfront payments alone. Regardless, these results are consistent with *H2a*, which predicts that greater difficulty in monitoring inventor effort will be associated with greater reliance on revenue-based royalty rates.

The interactions of the citations after agreement date with the number of patents held by the two parties are not significantly correlated with r and f – suggesting that inventors and developers may not be using the terms to signal the inventions’ hidden quality as anticipated by *H1a* and *H1b*.

Although not directly related to the hypotheses, the estimated effects of some control variables are interesting. For example, more experienced developers prefer higher f and universities receive both lower f and r relative to other types of inventors, *ceteris paribus* (relative to U.S. corporations, the omitted inventor and developer organizational type). The former result suggests that experienced developers are less risk-averse (or less capital-constrained) and prefer to pay upfront rather than share their revenues. The result on university inventors may be driven by either differences in institutional objectives or levels of sophistication in license negotiations. Parties also appear to trade off territorial restrictions for royalty rates. Licenses with patents that have been litigated receive more than twice the f that other licenses do. This result provides additional support to the symmetric information model: all parties to a license are more likely to be aware of the value of a patent or patents after litigation proceedings.

1.5.3 Results for minimum royalty payments and milestone payments

Table 1.8 reports Tobit estimates of the effect of RHS variables on log minimum royalty payments and log milestone payments.³⁷

The interaction term of inventor patents in the same subclass as licensed patents (proxying for privately informed inventor) and post-agreement “unexpected” citations (proxy for hidden quality) is directly related to minimum royalty payments (significant at $p < 0.05$). Hence, asymmetrically informed inventors appear to signal high quality inventions by requiring higher minimum royalty payments rather than higher running royalties as anticipated in *H1a*. The presence of a due-diligence clause is also associated with an increase in the amount of net minimum royalty payments (significant at $p < 0.05$). Since citations at license date are positively related to f and negatively related to p , it appears that symmetric information on quality increases upfront fees but decreases minimum royalty payments, broadly consistent with *H0*.

The proxy for hidden quality (unexpected citations without licensor or licensee patents interactions) is positively correlated with the magnitude of milestone payments, but inventor knowledge of the invention’s hidden quality (proxied by the interaction term of citations

³⁷ Estimates not reported here suggest that the effect of the RHS variables on the probability of observing p and m payments and the magnitude of p & m , conditioned on censoring, are similar.

post-agreement date and inventor patents in the same subclass as the licensed patents) is negatively related to milestone fees. This may be because asymmetrically informed inventors substitute p for m to avoid developer moral hazard concerns. These results suggest that milestone payments are driven by symmetric uncertainty related to the quality of the licensed invention. Higher shares of references to scientific literature in licensed patents, used here as a proxy for embryonic inventions, and the presence of know-how clauses, are also positively associated with milestone payments.

1.5.4 Robustness checks

The theoretical models assume that the different types of contractual payments are substitutes for each other (assumption *A5*). Thus upfront fees, royalties (royalty rates or minimum royalty payments), and milestone payments should be negatively related to each other for a given level of revenues. This implication of theory is not unambiguously supported by the estimates – for example, the estimated positive effect of unobservable developer actions on f is not accompanied by a significantly negative effect on r . This suggests that the payment terms (f & r) are not perfect substitutes for each other in the real world. Alternatively, the payments are simultaneously determined, and the theoretically predicted negative relationship among the different terms is part of the error term in the independent OLS equations for the different payments.

I investigate simultaneity bias by estimating the effects of imperfect information variables on each payment term, holding constant the level of all other payment terms in the contracts. Regression estimates of the effects of explanatory variables and other payments on each payment term (f , r , p , m) are reported in Table 1.9. These partial correlations are over and above the effects of the quality and effort variables and should pick up relationships among payment terms previously subsumed in the error term. f and r are not negatively correlated with each other, but m and p appear to be imperfect substitutes (at $p < 0.05$). Most importantly, the estimates show that the introduction of other fees does not alter the previous findings on the effect of hidden quality and unobservable effort proxies, ruling out simultaneity bias as an issue in the estimations. Further, a Seemingly Unrelated Regression system of equations specification (unlike OLS, SUR allows errors from each of the four contractual payment equations to be correlated with each other) also yields coefficient estimates that are qualitatively similar to the OLS and MLE (Tobit) estimates reported here.

However, the issue of the real relationship between the different payment terms remains. One explanation for the empirical pattern of relationships may be that license negotiators do not have precise expectations about future revenues, obscuring the theoretically anticipated relationship among r and the other payment terms. This view is supported by the sample distribution of royalty rates, which does not display the large variance associated with a wide dispersion of expected revenues of sample inventions and other payments. Indeed, Figure 1.1 shows that much of the sample variation in r is explained by the presence of know-how and show-how clauses, and values of r “clump” around the respective median values for show-how, know-how and ordinary licenses.³⁸ Licensing executives I interviewed revealed

³⁸ Consistent with my findings, Allen and Lueck (1993) report 92% of contracts between landowners and tenants share output on a 50/50, 40/60, or one-third/two-thirds basis, obscuring a clear relationship between upfront and revenue-based payments. Lafontaine and Shaw (1999) and Lafontaine (1992) also

that they decide royalty rates by initially relying on rules of thumb or “comparables” (to account for the transfer of inventor codified and tacit knowledge) and then divide expected downstream rents among fixed fees, minimum royalties, and milestone payments as a function of information conditions and bargaining power (P.C. on 10.18.09 with Lorraine Morrison, Licensing Executives Society).

1.6 Concluding remarks

This study has empirically evaluated the predictions of classical agency theories about the effect of imperfect information on contractual payment schemes. My findings agree with, and depart from, the theoretical predictions as follows.

First, moral hazard models view the transfer of inventor tacit knowledge to developers as involving unobservable actions, and recommend compensating the inventor with “pay for performance.” In this spirit, Jensen & Thursby (2001) link unobservable inventor effort in development to higher revenue-based royalty rates. The finding that biomedical inventors’ visible efforts to transfer “codified” know-how are compensated with higher upfront fees and milestone payments, while the transfer of hard-to-observe “tacit” knowledge is associated with higher royalty rates, is consistent with the Jensen-Thursby prediction. Inventors deal with the hazard of developer opportunism by demanding higher upfront payments, a finding also consistent with the prediction of 2-sided moral hazard models. These results reveal how sophisticated parties use different contractual provisions to transfer inventors’ tacit knowledge, in contrast to codified know-how – an issue of central concern to technology transfer executives and the innovation management literature (Arora 1995, Teece 1986).

Second, according to adverse selection models (Gallini and Wright 1990), privately informed inventors with valuable inventions signal their quality by offering contracts with higher royalty rates and lower upfront payments. The signaling hypothesis is not supported by the royalty rates for my sample contracts, but is consistent with the results for minimum royalty payments. The shortcomings of royalty rates as signals for hidden quality were highlighted in my interviews with licensing executives. Inventors are required to estimate (*ex ante*) and verify (*ex post*) developers’ final revenues to use royalty rates as signals of their invention’s quality. The estimation of product revenues is costly because of substantial uncertainties about the success and scope of inventions at agreement date, and verification of final product revenues taxes the limited resources of specialized inventors. By contrast, minimum royalty payments are relatively easy to specify and verify, and their presence in license contracts appears to represent a real-world adaptation to the drawbacks of royalty rates. The finding also is consistent with the view of industry practitioners that hidden information about quality held by the inventor relates to the feasibility of developing and marketing the invention, rather than private information about market size. By contrast, theoretical models frequently cite the importance of private information about revenues. Minimum royalty payments, which are contingent on commercialization, address developer concerns about the

fail to find a negative relationship between royalty rates and upfront fees in a sample of franchising agreements.

inventors' private information about the feasibility of inventions without the transaction costs and distortive effects of running royalties. Future theories can thus model verifiability concerns, as well as the specific nature of asymmetric information, in examining why royalty rates are used to address unobservable effort but not inventors' private information about quality.

Third, milestone payments are directly related to the unexpected quality of inventions at agreement date. This finding is inconsistent with the view that milestone fees are substitutes for royalty rates in addressing inventor moral hazard (Dechenaux *et al* 2009). Licensing executives view milestones (*e.g.* success in various phases of clinical trials, regulatory approval) as unpredictable "lotteries," and milestone payments as instruments for managing uncertainty associated with the feasibility of early-stage "blockbuster inventions" rather than as devices for compensating inventor effort (P.C. on 08.29.09 with Irwin Mettler, Office of Technology Licensing, University of California, Berkeley).³⁹ Finally, upfront fees, unlike milestone payments vary directly with information about the invention's quality available to both inventors and developers at agreement date – a finding anticipated by theories of licensing with symmetric information (*e.g.* Kamien & Tauman 1986 and Katz & Shapiro 1986).

The findings of this study therefore suggest that sophisticated value-maximizing agents respond to information hazards in ways that are broadly consistent with the prescriptions of agency theory. The relationship between information and the structure of contracts is more complicated than portrayed by theory, however, and is reflected in the prominence of alternative provisions such as minimum royalty and milestone payments.

³⁹ Another fact consistent with the view that milestone payments address technical uncertainties associated with embryonic inventions is that university inventions commonly involve milestone payments. These licenses rarely stipulate inventor involvement in developer's downstream activities because most universities do not contract out faculty know-how (only 8% of university licenses specified a "show-how" clause as compared to 22% for the rest of the sample) suggesting that uncertainties about quality, not inventor moral hazard drives milestone payments.

Chapter 1 Figures and Tables

FIGURE 1.1: BOX PLOT OF SAMPLE ROYALTY RATES BY LICENSE TYPE

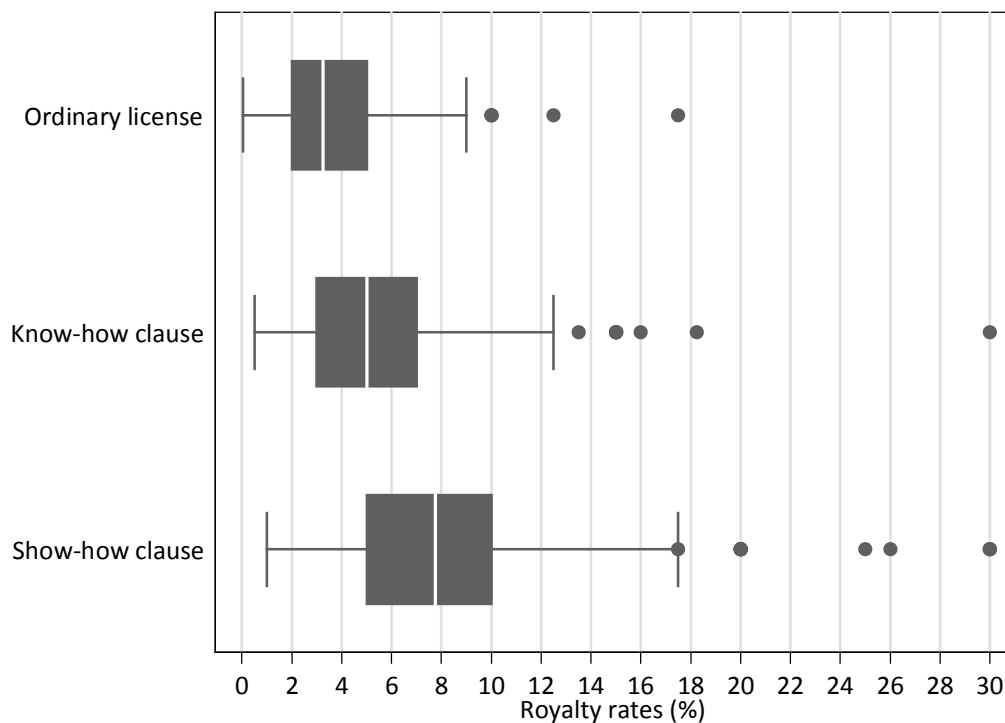


FIGURE 1.1 NOTES: The lines in the boxes represent median values for each category (ordinary license = 3.25%, know-how license = 5%, show-how license = 7.75%) among the 505 sample licenses. Lower and upper hinges of boxes represent respectively 25th and 75th quartile values. Lower and upper whiskers represent the lowest datum within 1.5 IQR of the lower quartile, and the highest datum still within 1.5 IQR of the upper quartile respectively. Dots represent outlying observations.

TABLE 1.1: AGENCY THEORY PREDICTIONS ABOUT CONTRACTUAL
UPFRONT FEES & ROYALTY RATES

Theory model	Variable	Informed inventor	Informed developer
Symmetric information (Kamien & Tauman 1986)	Quality		(+, 0)
Adverse selection (Gallini & Wright 1990, Beggs 1992)	Hidden quality	(-, +)	(+, -)
Moral Hazard (Jensen & Thursby 2001)	Unobservable effort	(-, +)	(+, -)

TABLE 1.1 NOTES: The theory models all assume risk neutral parties. Symmetric information and adverse selection theories respectively relate commonly known quality and privately known quality of the invention to upfront fees (f) and royalty rate (r). Moral hazard theories relate unobservable effort of the parties to (f, r) .

TABLE 1.2: THERAPEUTIC CATEGORIES OF SAMPLE LICENSES

Therapeutic Category	N of licenses	Expected annual revenues
<i>Pharmaceuticals</i>	244 (48.3%)	
Anticancer, General Agents	24	>US\$1 B
Anticancer, Immunological	16	US\$2-5 B
Drug formulation technology	16	NA
Antibiotics	11	US\$0.5-2 B
Antiinfective	11	US\$0.5-2 B
Antiviral, Other	10	US\$2-5 B
Unclassified	10	NA
Gastrointestinal disorders	9	US\$0.5-2 B
Neurological	9	US\$2-5 B
Imaging Agent	8	<US\$0.5 B
Monoclonal Antibodies	8	>US\$1 B
Prophylactic Vaccine	8	US\$2-5 B
Antidiabetic	7	US\$2-5 B
Dermatological	7	>US\$10 B
Antiviral, Anti HIV	6	US\$0.5-2 B
Cardiovascular	6	US\$10 B
Radio/Chemoprotective	6	<US\$0.5 B
Therapeutic Vaccine	6	US\$0.5-2 B
Vulnerary products	6	US\$0.5-2 B
Antithrombotic	5	US\$2-5 B
Cellular therapy	5	NA
Nutritional supplements	5	US\$0.5-2 B
Analgesic	4	US\$5 -10B
Anticancer, Antibiotic	4	US\$2-3 B
Antiinflammatory	4	>US\$10 B
Cognition enhancer	4	US\$0.5-2 B
Musculoskeletal	4	US\$5 -10B
Anaesthetic	3	US\$0.5-2 B
Antiviral, Interferon	3	<US\$0.5 B
Immunostimulant	3	<US\$0.5 B
Addiction treatment	2	US\$0.5-2 B
Antianaemic	2	US\$2-5 B
Anticancer, Alkylating	2	US\$0.5-2 B
Anticoagulant	2	US\$0.5-2 B
Antidepressant	2	>US\$10 B
Antiparkinsonian	2	US\$0.5-2 B
Antipruritic	2	<US\$0.5 B
Haematological	2	US\$2-5 B

TABLE 1.2: Continued

Therapeutic Category	N of licenses	Expected annual revenues
<i>Devices and Instruments</i>	<i>224 (44.4%)</i>	
Catheters, Needles & Syringes	29	NA
Cardiovascular devices	17	>US\$10 B
Diagnostic Imaging products	16	>US\$10 B
Wound Care products	16	>US\$10 B
Diagnostic (in-vitro) products	15	US\$0.5-2 B
Laser (Medical)	14	US\$2-5 B
Ophthalmic Devices	13	>US\$10 B
Analytical Instruments	11	NA
Stents	11	>US\$1 B
Medical plastics	10	NA
Minimally invasive surgical devices	9	>US\$10 B
Urology devices	8	NA
Kits and Trays	7	<US\$0.5 B
Patient Monitoring systems	7	US\$0.5-2 B
Laboratory equipment	6	NA
Unclassified	6	NA
Electrophysiology products	4	NA
Implanting technology	4	NA
Dialysis products	3	US\$5 -10B
Endoscopy	3	>US\$10 B
Male sexual dysfunction	3	US\$2-5 B
Orthopedic products	3	>US\$10 B
Respiratory	3	>US\$10 B
Defibrillators	2	NA
Dental products	2	US\$5 -10B
Hearing aid devices	2	US\$0.5-2 B
<i>Genetics</i>	<i>28 (5.5%)</i>	
Gene Therapy	15	US\$2-5 B
Cloning technology	13	NA
<i>Veterinary</i>	<i>9 (1.8%)</i>	NA
TOTAL	505	

TABLE 1.2 NOTES: The therapeutic categories and their revenue potential were identified by matching descriptions of the 505 sample inventions to descriptions in Pharmaprojects (for pharmaceutical inventions) and the Medical & Healthcare Marketplace Guide (for medical devices and instruments).

TABLE 1.3: ORGANIZATIONAL FORMS OF SAMPLE INVENTORS AND DEVELOPERS

Organization type	Inventor	Developer
US Corporation	46.9%	86.7%
US University	21.8%	-
Foreign Corporation	10.1%	9.5%
US Individual	10.5%	-
Others	10.7%	3.8%
Total Sample Licenses	505	505

TABLE 1.3 NOTES: “Others” category includes U.S. non-profits, foreign universities and foreign individuals.

TABLE 1.4: ASSIGNEE TYPES OF IN-SAMPLE AND OUT OF-SAMPLE
U.S. PATENTS

	In-sample patents	Out of sample patents
<u>PANEL A: Organization type</u>		
US for-profit organization	46.2%	45.0%
US University	23.2%	11.3%
Foreign for-profit organization	12.2%	30.6%
US Individual (Unassigned inventor)	14.5%	11.1%
US Federal Government	3.8%	1.6%
Foreign governments	0.0	0.4%
Total patents (grant years 1976-2008)	1,265	170,955

<u>PANEL B: Patent citations</u>		
At date of license		
Mean	8	4.97
SD	16.9	8.32
Median	1	1.52
After date of license		
Mean	21.4	10.6
SD	68.1	20.2
Median	8	5.57

TABLE 1.4 NOTES: PANEL A compares the distribution of assignee organization types among the sample and “out of sample” patents in the USPTO patent subclasses of the sample patents. The 1,265 sample patents were associated with the 505 sample licenses. Assignee organization types are gathered from USPTO records. All numbers except total patents are percentages.

PANEL B compares the citations of the sample and “out of sample” patents. Out of sample patents are matched by the USPTO patent subclasses of the sample patents and citations of out of sample patents are calculated in the same time-window as the sample patents.

TABLE 1.5: SAMPLE SUMMARY OF PAYMENT TERMS

Revenue-sharing terms	Non-zero N	Median	Mean	SD
Royalty Rate (%)	100%	5.0	5.5	4.3
Upfront fees (Y2008 1,000\$)	72.6%	214.4	1,546.1	5,824.4
Min. royalty payments (Y2008 1,000\$)	39.8%	414.5	1,643.8	3,978.0
Milestone payments (Y2008 1,000\$)	26.9%	1,255.0	4,034.8	8,733.1

TABLE 1.5 NOTES: The table presents summary statistics for the contractual payment terms (dependent variables) in the 505 sample licenses. Royalty rates are expressed in percentages and the rest of payments in 1000's of FY2008 constant dollars. Minimum royalty payments are NPV values of annual minimum royalty payments over the term of the agreement discounted at 5% p.a. Milestone payments are the sum of state-contingent payments. Sample-statistics reported are for non-zero values of the respective revenue-sharing terms.

TABLE 1.6: SAMPLE SUMMARY OF EXPLANATORY AND CONTROL VARIABLES

<i>PANEL A: Quality-related variables</i>			
	Median	Mean	SD
Normalized citations at license date	1.00	1.42	1.80
Normalized citations after license date	1.51	4.62	12.43
Licensor patents in subclasses of licensed patents	0	1.67	5.63
Licensee patents in subclasses of licensed patents	0	0.38	1.51
<i>PANEL B: Effort-related variables</i>			
Know How (0/1)	41.2%		
Show How (0/1)	18.6%		
Due Diligence (0/1)	35.8%		
<i>PANEL C: Other license characteristics</i>			
	Median	Mean	SD
Number of patents per license	2	2.88	2.80
Term of license in years	16	14.9	4.9
Normalized % of science references	1	1.2	1
	Non-zero N		
Exclusivity			
	Non Exclusive (0/1)	17.2%	
	Exclusive (0/1)	44.9%	
	Exclusive to field of use (0/1)	37.8%	
Territorial restrictions (0/1)		12.9%	
Litigated (0/1)		4.3%	
<i>PANEL D: Inventor and developer characteristics</i>			
	Median	Mean	SD
Inventor Inventive age	12	16.0	12.9
Developer Inventive age	6	7.9	8.8

TABLE 1.6 NOTES: The table presents summary statistics for the Right Hand Side variables (independent and control variables). All statistics in the panels are for the full sample of 505 licenses. PANEL A: Citations are normalized by dividing the number of citations received by each licensed patent by the number of citations of the “average” patent in the same issue year and USPTO patent subclass as the licensed patent. For licenses with more than one patent, I use the average value of the patents’ normalized citations. Licensor and licensee patents are the number of the respective parties’ patents in the same USPTO patent subclass as licensed patents. PANEL B: Variables are dichotomous and indicate the presence of Know-how, show-how and due-diligence clauses in the licenses. PANEL C: Science references are the percentage of backward citations or references to scientific papers in licensed patents. Normalization follows the procedure explained under PANEL A notes. PANEL D: Licensor and licensee “innovative” ages are calculated as the difference between license date and the application date of the parties’ earliest U.S. patent application.

TABLE 1.7: REGRESSION ESTIMATES OF EFFECTS OF HIDDEN QUALITY & UNOBSERVABLE EFFORT PROXIES ON UPFRONT FEES & ROYALTY RATES

Model	Variable	Predicted (f, r)	[1] log upfront	[2] royalty rate
Symmetrically known quality	Citations at license date	(+, 0)	0.204*** [0.079]	-0.021 [0.090]
Inv. informed of hidden quality	Citations after license date X Log Inv. Patents	(-, +)	0 [0.010]	0.006 [0.014]
Dev. informed of hidden quality	Citations after license date X Log Dev. Patents	(+, -)	-0.039 [0.026]	-0.005 [0.018]
Observable Inventor effort	Know-how clause	(+, 0)	0.924** [0.407]	1.268*** [0.350]
Unobservable Inventor effort	Show-how clause	(0, +)	0.668 [0.501]	4.850*** [0.614]
Unobservable Developer effort	Due-diligence clause	(+, -)	1.230*** [0.371]	-0.525 [0.427]
	Citations after license date		0.013 [0.017]	0.005 [0.014]
	Log inventor patents		0.245 [0.269]	0.277 [0.259]
	Log developer patents		-0.506 [0.509]	-0.278 [0.399]
	No. of licensed patents		0.055 [0.062]	-0.157*** [0.060]
	Litigated patents in license?		2.736*** [0.764]	0.209 [0.795]
	% of science references		0.028 [0.172]	-0.158 [0.194]
	Exclusive		0.66 [0.583]	-0.361 [0.546]
	Exclusive to field		0.445 [0.580]	0.571 [0.647]
	Territorial restrictions		0.226 [0.519]	1.901*** [0.715]
	Log Trend		0.159 [0.275]	0.228 [0.262]

Contd.

TABLE 1.7: Continued

Variable	[1] log upfront	[2] royalty rate
Log Inventor age	0.277 [0.202]	0.107 [0.197]
Log Developer age	0.574*** [0.167]	0.052 [0.175]
Inventor Foreign Corp	-0.1 [0.654]	-0.435 [0.704]
Inventor Others	-0.386 [0.581]	-2.988*** [0.583]
Inventor US Individual	-0.799 [0.722]	-1.777*** [0.632]
Inventor US University	-1.348** [0.547]	-1.747*** [0.590]
Developer Foreign Corp	1.252** [0.588]	-0.18 [0.526]
Developer Others	1.586* [0.963]	-0.978 [0.977]
Therapeutic class dummies	Y	Y
Constant	0.043	4.697
Observations	505	505
R-squared		0.42
Log-likelihood	-1086.1	
Robust standard errors in brackets; * p<0.1; ** p<0.05; *** p<0.01		

TABLE 1.7 NOTES: Columns [1] & [2] report MLE (Tobit) and OLS estimates of the effect of RHS variables on $\log(1+\text{Upfront fees})$ and royalty rate (in %) respectively. Upfront fees are in 1000's of FY2008\$. All estimations include 65 therapeutic category dummy variables. "U.S. corporations" is the reference organizational form (for both inventors and developers) and omitted from the estimations.

TABLE 1.8: MLE (TOBIT) ESTIMATES OF EFFECTS OF HIDDEN QUALITY & UNOBSERVABLE EFFORT PROXIES ON MINIMUM ROYALTY & MILESTONE PAYMENTS

Model	Variable	[1] log min royalties	[2] log milestone
Symmetrically known quality	Citations at license date	-0.562** [0.235]	0.072 [0.417]
Inv. informed of hidden quality	Citations after license date X Log Inv. Patents	0.047** [0.020]	-0.096** [0.039]
Dev. informed of hidden quality	Citations after license date X Log Dev. Patents	-0.004 [0.042]	-0.043 [0.056]
Observable Inventor effort	Know-how clause	0.293 [0.783]	2.667*** [1.016]
Unobservable Inventor effort	Show-how clause	-1.341 [1.027]	-0.963 [1.417]
Unobservable Developer effort	Due-diligence clause	1.607** [0.729]	1.635* [0.968]
	Citations after license date	-0.056 [0.035]	0.110*** [0.031]
	Log inventor patents	0.091 [0.509]	0.599 [0.707]
	Log developer patents	-0.657 [1.034]	-0.641 [1.072]
	No. of licensed patents	0.093 [0.119]	0.047 [0.156]
	Litigated patents in license ²	-3.021* [1.689]	0.19 [3.071]
	% of science references	0.064 [0.333]	0.939** [0.396]
	Exclusive	-0.46 [1.136]	8.472*** [1.813]
	Exclusive to field	0.549 [1.166]	7.844*** [1.853]
	Territorial restrictions	0.015 [1.083]	-0.092 [1.331]
	Log Trend	-1.479*** [0.547]	1.886** [0.914]

Contd.

TABLE 1.8 Continued

Variable	[1] log min royalties	[2] log milestone
Log Inventor age	-0.364 [0.385]	1.044* [0.595]
Log Developer age	-0.402 [0.322]	1.309*** [0.376]
Inventor Foreign Corp	-2.642* [1.416]	-1.563 [1.551]
Inventor Others	2.935*** [1.118]	1.118 [1.404]
Inventor US Individual	0.085 [1.265]	-7.603*** [2.381]
Inventor US University	3.405*** [1.010]	-3.026** [1.469]
Developer Foreign Corp	0.433 [1.232]	1.722 [1.479]
Developer Others	-1.401 [1.724]	3.143 [2.153]
Therapeutic class dummies	Y	Y
Constant	8.347	-25.691
Observations	505	505
Log-likelihood	-781.1	-572.01
Robust standard errors in brackets; * p<0.1; ** p<0.05; *** p<0.01		

TABLE 1.8 NOTES: Columns [1] & [2] report MLE (Tobit) estimates of the effect of RHS variables on $\log(1+\text{minimum royalty payments})$ and $\log(1+\text{milestone payments})$ respectively. Minimum royalty payments and milestone payments are in 1000's of FY2008\$. Estimations in Column [1] include the full set of 65 therapeutic category dummy variables. Estimations in Columns [2] use a smaller set of 26 more broadly defined therapeutic categories because of the smaller number of uncensored observations. "U.S. corporations" is the reference organizational form (for both inventors and developers) and omitted from the estimations.

TABLE 1.9: REGRESION ESTIMATES OF EFFECT OF HIDDEN QUALITY & UNOBSERVABLE EFFORT PROXIES ON CONTRACTUAL PAYMENTS

Variables	[1] log upfront	[2] royalty rate	[3] log min royalties	[4] log milestone
Citations at license date	0.241*** [0.075]	0 [0.090]	-0.598** [0.243]	0.017 [0.417]
Citations after license date X Log Inv. Patents	-0.003 [0.010]	0.003 [0.014]	0.038* [0.021]	-0.090** [0.038]
Citations after license date X Log Dev. Patents	-0.035 [0.027]	-0.009 [0.018]	0.007 [0.049]	-0.026 [0.055]
Know-how clause	0.769* [0.395]	1.382*** [0.367]	0.258 [0.779]	2.577** [1.029]
Show-how clause	0.894* [0.514]	4.877*** [0.622]	-1.793* [1.067]	-0.274 [1.368]
Due-diligence clause	0.990*** [0.361]	-0.465 [0.435]	1.468** [0.721]	1.436 [0.957]
Citations after license date	0.015 [0.018]	0.009 [0.014]	-0.057 [0.037]	0.094*** [0.030]
Log inventor patents	0.259 [0.260]	0.291 [0.257]	0.056 [0.511]	0.574 [0.713]
Log developer patents	-0.492 [0.478]	-0.277 [0.405]	-0.724 [1.009]	-0.721 [1.040]
No. of licensed patents	0.04 [0.061]	-0.159*** [0.061]	0.088 [0.120]	0.021 [0.157]
Litigated patents in license?	2.909*** [0.819]	0.411 [0.819]	-3.800** [1.818]	-1.329 [3.451]
% of science references	-0.007 [0.171]	-0.135 [0.195]	0.103 [0.324]	0.842** [0.385]
Exclusive	0.331 [0.580]	-0.161 [0.578]	-0.33 [1.116]	8.430*** [1.774]
Exclusive to field	0.077 [0.592]	0.74 [0.690]	0.758 [1.155]	8.245*** [1.823]
Territorial restrictions	0.266 [0.512]	1.921*** [0.719]	-0.122 [1.079]	0.389 [1.288]
Log Trend	0.25 [0.272]	0.304 [0.267]	-1.464*** [0.550]	1.950** [0.909]

Contd.

TABLE 1.9: Continued

Variables	[1] log upfront	[2] royalty rate	[3] log min royalties	[4] log milestone
Log Inventor age	0.248 [0.196]	0.149 [0.199]	-0.38 [0.376]	1.114** [0.561]
Log Developer age	0.552*** [0.165]	0.118 [0.177]	-0.462 [0.323]	1.153*** [0.364]
Inventor Foreign Corp	0.156 [0.646]	-0.404 [0.711]	-2.593* [1.375]	-2.291 [1.556]
Inventor Others	-0.698 [0.580]	-3.025*** [0.593]	3.639*** [1.139]	0.876 [1.453]
Inventor US Individual	-0.583 [0.710]	-1.903*** [0.635]	0.589 [1.269]	-7.590*** [2.062]
Inventor US University	-1.492*** [0.545]	-1.969*** [0.615]	3.909*** [1.005]	-2.711* [1.503]
Developer Foreign Corp	1.180** [0.578]	-0.112 [0.535]	0.127 [1.193]	1.368 [1.471]
Developer Others	1.563 [0.980]	-0.811 [0.967]	-1.422 [1.802]	3.046 [2.066]
log upfront		-0.037 [0.066]	0.453*** [0.134]	0.510*** [0.152]
royalty rate	-0.028 [0.048]		0.043 [0.088]	-0.335*** [0.130]
log min royalties	0.237*** [0.057]	0.055 [0.059]		-0.345** [0.142]
log milestone	0.169*** [0.054]	-0.103 [0.065]	-0.282** [0.120]	
Therapeutic class dummies	Y	Y	Y	Y
Constant	-0.76	4.298	6.381	-24.287
Observations	505	505	505	505
R-squared		0.43		
Log-likelihood	-1073.3		-772.1	-561.98

Robust standard errors in brackets; * p<0.1; ** p<0.05; *** p<0.01

TABLE 1.9 NOTES: The columns report MLE (estimates) of the effect of RHS variables on $\log(1+\text{Upfront fees})$, $\log(1+\text{Minimum royalty payments})$ and $\log(1+\text{milestone payments})$, and OLS estimates of the effect of RHS variables on royalty rate. Upfront fees, minimum royalty payments and milestone payments are in 1000's of FY2008\$ and royalty rate is expressed in percentages. All estimations, except the milestone payments equation, include 65 therapeutic category dummy variables. The milestone payment equation includes 26 category dummy variables. "U.S. corporations" is the reference organizational form (for both inventors and developers) and omitted from the estimations.

Chapter 2

Political influence behind the veil of peer review: an analysis of public biomedical research funding in the U.S.

2.1 Introduction

How do politicians concentrate federal benefits in their constituencies when reputational concerns constrain them from making direct transfers to their constituents? An immense amount of research has focused on the transfer of such benefits as rivers and harbors projects, defense contracts, and academic earmarks by Congressmen to their constituencies (see Alvarez and Saving's [1997] review).⁴⁰ However, the absence of a counterfactual allocation mechanism for federal benefits makes it difficult to assess the distributive effect of political influence in these studies. A second strand of literature observes that politicians make "indirect" transfers to interest groups when the reputational penalty for making indirect transfers is less than that for making direct transfers (Tullock 1983, Coate and Morris 1995). Again, there is very little empirical analysis of indirect transfers or on the relationship between the form of transfers and the concentration of constituency benefits.

This study addresses the deficiencies posed above by analyzing federal funding for biomedical research in the U.S., which amounted to \$28.7 billion for fiscal 2008.⁴¹ The National Institutes of Health (NIH), the agency responsible for biomedical research, supports half of all federal nondefense R&D and over 60% of federal R&D in U.S. universities (AAAS 2009). The NIH allocates funds among research performers by a mechanism based on "peer review" of the scientific merit of performers' research proposals and is considered an exemplar research agency because of its avoidance of politically mandated performer-specific earmarks (AAAS 2008).

Congressional appropriations bills and committee meeting reports reveal that although committee members do not earmark allocations to biomedical research performers, they frequently support specific biomedical research fields and projects. I argue that members seeking to favor their constituents transfer federal resources to those biomedical fields that are most likely to reach research performers in their constituencies. Such indirect transfers

⁴⁰ The premise of this research stream on distributive politics is that politicians seek to enhance their reelection prospects by transferring federal benefits to their constituencies. Congressional institutions such as committees are structured to facilitate these transfers (Mayhew 1974, Ferejohn 1974, Fiorina 1977 Weingast and Marshall 1988).

⁴¹ NIH accounts for 20% of all federal R&D which in FY2008 was estimated to be 1% of GDP (AAAS 2009).

to members' constituencies, couched in the form of patronage for particular research topics, are more palatable to the scientific community and the public than direct transfers to performers that bypass the peer review procedure for distributing research funds.

I test whether research performers in the states of appropriations committee members receive a higher level of peer-reviewed biomedical research funds by using data on all grants awarded by the NIH to 8,310 external research performers between the years 1984 and 2003 – a period during which federal support for the agency grew from \$8.4 billion to \$30.2 billion (Constant FY2008 Dollars, see AAAS 2009). I exploit the panel structure of the data to control for the unobservable characteristics of biomedical research performers (or states) that may be correlated with both their receipts of federal research funds and representation in appropriations committees.

I find each additional member on the House subcommittee that deals with NIH appropriations (the Labor, Health and Human Services, Education, and Related Agencies or the “LHHE” subcommittee of the House Appropriations Committee) is associated with a 5.9% increase in NIH research funding for represented institutions. State universities, which receive the largest share of federal biomedical research funds (41.5% of all NIH extramural awards in FY2003), and small businesses are especially benefitted by House-LHHE representation, receiving increases of 8.8% and 10.3% per House-LHHE member respectively. Representation on the House and Senate appropriations committees is associated with transfers of 2.9 to 6.7% of total NIH extramural research grants for the period of this study. \$0.9 billion of the \$20 billion worth of peer-reviewed extramural awards made by the NIH in the year 2003 can be attributed to the constituency interests of HAC LHHE representatives.

Does political representation favor R&D performers in those fields of research in which they are relatively “strong,” or fields in which performers receive relatively lower funds? I find that research performers in the lowest two quartiles of grant recipients in any biomedical field average a 3.6% - 6.4% increase for research in those fields from House LHHE representation. Research fields in which represented performers are strong do not receive larger allocations than otherwise comparable, but unrepresented performers. Peer review that is not moderated by political representation concentrates funding in the top-quartile research fields of performers. These findings highlight a tension between the distributive effects of merit-driven allocations and politically motivated transfers – a topic of debate in U.S. science policy at least since Vannevar Bush's 1945 proposal for a politically insulated public R&D system.

The remainder of the paper is organized as follows. Section 2.2 describes the congressional and bureaucratic institutions that affect the transfer of public funds to biomedical research performers. Section 2.3 specifies the empirical model and discusses my data. Section 2.4 reports estimates of committee member influence, robustness checks, and ancillary results. Section 2.5 examines the effects of committee representation on funding for the stronger and weaker fields of research performers. Section 2.6 concludes by discussing the implications of political oversight of the American public biomedical R&D enterprise.

2.2 An overview of the Congressional appropriations process for biomedical research

Politicians in Congressional committees responsible for the allocation of federal resources trade off the electoral benefits of concentrating resources in their constituencies against the reputational consequences of favoritism. Reputational penalties can be imposed by the Congress, which has the power to vote against committee actions, or by other groups that are harmed by committee members' allocation decisions. Politicians may hence prefer "disguised" methods of transfers to avoid detection by the public of the real motivation for transfers. Tullock (1983) calls such methods "indirect transfer mechanisms" and cites as an example a politician who supports the construction of a road routed so as to increase the value of certain pieces of real estate, rather than directly transferring cash to the real estate owner and locating the road optimally (Coate & Morris 1995).⁴²

Do congressional appropriators of biomedical research funds rely on indirect transfer mechanisms to benefit research performers in their constituencies by supporting certain research topics and projects? I address this question in two distinct parts that deal respectively with the form and effect of political transfers. The first part examines the appropriations process and the grant allocation system at the NIH, and characterizes the form of transfers to research performers. I find that unlike bills associated with other agencies, appropriations bills related to the NIH rarely if ever include performer-specific earmarks. Subcommittee meeting reports related to NIH appropriations nevertheless include extensive language supporting specific research topics and projects, which operates as an indirect transfer mechanism. The second part statistically tests whether the peer-reviewed grants made by the NIH are concentrated in committee members' constituencies.

2.2.1 The National Institutes of Health and biomedical research

The National Institutes of Health is a part of the U.S. Department of Health and Human Services and provides 85% of total federal support for R&D in the biological, medical, and psychological sciences (based on FY2004 federal obligations, NSF 2008). More than 80% of the agency's funding is awarded annually through competitive grants to researchers at over 3,000 universities, medical schools, and other research institutions (the rest of the funds support "intramural" research and miscellaneous activities at the NIH). NIH funding has led to numerous fundamental discoveries, including the first vaccine to prevent cervical cancer, the first implantable permanent artificial heart approved by the FDA, the first trial of gene therapy in humans, identification of the first drug to show efficacy against HIV, and sequencing of the human genome (The NIH Almanac 2007).

⁴² In a political economy model, Coate & Morris (1995) show how uncertainty among voters about the effect of different transfer policies and the type of politicians can result in indirect transfers that are inefficient. The authors cite public projects such as the construction of dams and rivers or earmarks as examples of indirect transfers (see p 1227). Yet, in reality there is little uncertainty about the intended beneficiaries of typical "pork barrel" projects, or their benefits to the rest of the society. The case considered here more accurately illustrates indirect transfers because the public is not well-informed of the effects of allocating money for research in different biomedical research fields.

The NIH is organized into 27 independent research institutes and centers listed in Table 2.1. Institutes specialize by disease (*e.g.* National Cancer Institute), organ (National Eye Institute), field of science and medicine (*e.g.* National Institute of General Medical Sciences), or by stages of human development (*e.g.* National Institute on Aging) (McGeary and Smith [2002] provide an excellent description of the NIH's organizational structure).

The Institutes at the NIH utilize a “dual peer review” process to evaluate research proposals. In the first stage of this process, grant applications are evaluated by panels of non-federal scientists in relevant scientific disciplines and research areas. These experts score applications based on their significance, technical merit, innovativeness, and investigators' qualifications. Each application is then assigned a single “priority score,” the average of all experts' scores. Applications with scores below a predetermined cutoff do not advance to the second stage and are not recommended for funding. Acceptable applications are assigned to the NIH institute or center best suited to fund the research where they are reviewed in a second round by a “National Advisory Council” composed of scientists and public representatives. Each Institute/Center's Advisory Council recommends applications for funding by considering priority scores and the proposed project's relevance to the Institute's mission. The Director of the Institute/Center makes the final funding decision based on the relevant Advisory Council's recommendation (NIH 2008).

2.2.2 The Congressional appropriations process and the NIH

Although Institutes within the NIH allocate grants to research performers, the allocation of federal funds among Institutes is the result of a complex process of negotiations among the NIH director, Office of Management and Budget (OMB), Department of Health and Human Services (DHHS), and the Congress. Budget requests are assembled by the individual Institutes in negotiations with the NIH Director and staff. The Director of the NIH then negotiates with the Department of Health and Human Services and the Office of Management and Budget within the Executive Office of the President to craft a budget request for the NIH that is consistent with White House priorities. The resulting “President's budget request” is submitted to the Congress.

The bulk of annual congressional decision making on presidential budget requests for federal agencies takes place in the appropriations committees of the House and Senate, especially within the relevant subcommittee of each chamber's appropriations committee. In the House Appropriations Committee (HAC), the NIH budget request is handled by the Labor, Health and Human Services, and Education and Related Agencies Subcommittee (LHHE). A similarly named subcommittee of the Senate Appropriations Committee (SAC) evaluates the NIH budget request in that chamber. Appropriations subcommittee members from both the House and the Senate separately discuss the President's budget request and seek inputs and clarifications from the NIH staff in “hearings” before drafting appropriations bills and reports. Subcommittee recommendations are voted on by the full appropriations committee and reported to the floor of each chamber. Differences between the House and

Senate appropriations bills, if any, are resolved through negotiations in a “conference committee,” producing a final appropriations bill that is voted on by Congress.⁴³

The bills reported out to the floor of the House and Senate by each chamber’s appropriations committee indicate the total appropriations figures for each of the NIH institutes and centers. Subcommittee meeting reports that accompany appropriations bills contain important additional detail and guidance on the disbursement of appropriations by the institutes and centers. According to David Minge, a former U.S. House Representative, language supporting earmarks and “pork barrel spending” in these reports often escape congressional or public scrutiny. Although the commentary in subcommittee meeting reports lacks the force of the law, federal agencies are attentive to the “guidance” provided in these reports since subcommittee members enjoy long tenures and have considerable power to punish deviant agencies in subsequent appropriations (Minge 2002 p116).

2.2.3 Indirect Political Transfers in NIH Appropriations

The appropriations subcommittee meeting reports for the “Departments of Labor, Health and Human services, and Education and Related Agencies” covering the 20 fiscal years between 1984 and 2003 provide fascinating insights into the breadth and depth of subcommittee members’ influence on the priorities, actions, and organization of the NIH. Senate and House LHHE subcommittee reports contain detailed directions to the Institutes on the following four types of transfers that directly affect the level of federal support for the different fields of biomedical research.

1. *Institute-level transfers.* At the broadest level, LHHE members alter the distribution of appropriations among NIH institutes and centers to reflect their biomedical research priorities. The inter-Institute distribution approved by the HAC and SAC LHHE subcommittees was different from the allocations requested by the NIH Director in all but four of the 20 appropriations bills that they produced between 1984 and 2003 (fiscal years 1996, 1997, 1998, and 1999 are the exceptions). For example, for FY1994, the House appropriated \$269 million more than the amount requested by the President for the NIH (total appropriations of \$10.94 billion). For that year, while all other institutes and centers received at least the amounts they sought, the National Center for Human Genome Research received less than its requested amount. Subcommittee reports may also recommend the creation of new institutes or centers that increase the level of funding for research areas supported by these new entities.
2. *Transfers among research fields.* Subcommittee support for particular fields of biomedical research often is related to concern over particular diseases. In every subcommittee report, research field-level specifications range in number from two for the smaller institutes and centers like the NIAAA to thirty for such large institutes as the NHLBI, NIDDK and NCI. Unlike reallocations of requested funds among Institutes that are described in appropriations bills, transfers within Institutes among research fields are rarely associated with specific

⁴³ The final appropriations authorized by the Congress for the NIH have exceeded the President’s requests by about 8% on average during the period of this study. Appropriations exceeding budget requests are unique to biomedical research, since the Congress, especially the HAC, commonly cuts budget requests.

dollar amounts and more often are indicated in the meeting reports that accompany appropriations bills through language “urging,” “recommending,” and “strongly supporting” increases or decreases for specific research areas. Members recommend new research fields for funding (Example 1) as well as support increased funding for specific research fields (Example 2).

Example 1: “Hemolytic Uremic Syndrome (HUS)..is caused by a bacterium that may be present in undercooked meat products which can result in sudden and severe digestive and kidney complications. The Committee encourages NIDDK to support research on HUS in order to develop effective treatments for the disorder.” House LHHE meeting report related to appropriations for NIDDK, FY1996

Example 2: “The Committee once again heard very moving testimony about Dystrophic Epidermolysis Bullosa from parents of children who are afflicted with this disease, as well as from some of its victims...The committee directs that a portion of the increased resources provided in this bill be used to encourage expanded research on Epidermolysis Bullosa and related diseases. The Committee requests a report, prior to hearings on the 1985 budget, as to how this directive has been carried out.” House LHHE meeting report related to appropriations for NIADDK, FY1984 (p 47).

3. *Transfers among research projects.* Project-level transfers support particular lines of research (Example 3) and/or research projects (Example 4) within a given disease field. Project-level advocacy tends to be highly targeted and accounts for a large proportion of the suggestions made by members to Institutes and Centers in committee reports.

Example 3: “The Committee notes favorably that NIAAA has publicized its intention to support research on the health effects of moderate wine and alcohol consumption at a significant funding level. The Committee urges NIAAA and other Institutes to support and assist research efforts in these areas, especially the impact of alcohol on cardiovascular health and longevity and on the dietary role of antioxidants and moderate alcohol consumption.” House LHHE meeting report related to appropriations for NIAAA, FY1996.

Example 4: “The Committee is encouraged by continued progress in developing oral chelators for the treatment of Cooleys anemia and strongly urges that this work be continued.” House LHHE meeting report related to appropriations for NHLBI, FY1992.

4. *Research performer-specific transfers.* The most specific of transfers indicate both the purpose and the recipient of research funding. These transfers are commonly known as “earmarks” and can be considered to be direct political transfers to research performers, in contrast to the more indirect transfers effected through the three mechanisms described above. The House-LHHE subcommittee reports contained no instances of performer-

specific earmarks during this period; Senate LHHE subcommittee reports contained the following two instances.

Example 5: "The Committee notes that retroviral infections in large domestic animals are excellent models for retroviral-induced diseases such as leukemia lymphosarcoma and AIDS in humans. The Committee believes that a retrovirus research center would well advance science and notes the expertise of Iowa State University in this field. The Committee directs that up to \$1,000,000 be made available for such a center." Senate LHHE meeting report related to appropriations for NCI, FY1992

Example 6: "The Committee has received information concerning the Appalachian region's need for a state-of-the-art cancer center in West Virginia. It has been estimated that about one-third of the West Virginians dying from cancer might have been saved by early diagnosis and treatment. This lack of organized statewide approaches to cancer prevention, detection, and accessibility to specialized care underscores the need for an academically-based cancer program for the State of West-Virginia. The committee directs that \$4.5 Million be used to facilitate the development of a cancer center at West Virginia University." Senate LHHE meeting report related to appropriations for NCI, FY1985 (p 55).

How do the four types of transfers described above relate to the constituency interests of LHHE members? The chair of the subcommittee responsible for the report incorporating Example 5 was Senator Tom Harkin from Iowa. Among the authors of the report that included Example 6 was Senator Robert C. Byrd of West Virginia – then the second most senior member of the Senate LHHE subcommittee. The West Virginia University now hosts a cancer center in its "Health Sciences Center" named after Robert C. Byrd. The University of California at San Francisco and Weill Medical College of Cornell University at New York were beneficiaries of NIH grants in 1996 and 1992 for research on the "beneficial effects of moderate wine consumption" and "oral chelators for the treatment of Cooleys anemia" respectively.⁴⁴ These grants may be associated with the project-level transfers illustrated in Example 3 and Example 4 and coincide with the appointment of the then relatively junior Representatives Nancy Pelosi of California and Robert J. Mrazek of New York to the HAC-LHHE.

While the existence of the Robert C. Byrd Health Sciences Center can be credibly attributed to Senator Byrd's representation on the LHHE, a causal link between grant recipients and subcommittee members is less compelling in the transfers among Institutes, research fields and projects. This is because the first three types of transfers, unlike performer-specific transfers, do not directly award funds to performers and are moderated by the NIH's peer review process. It is plausible that beneficiaries of these indirect transfers and representation in subcommittees are not causally related, but linked through factors such as the research

⁴⁴ Grant number 5R01AA011205-02 for project titled: "Antiatherogenic Effects of Moderate Alcohol Use"; Grant Number: 5R01HL043027-04 for project titled: "New Promise for Oral Iron Chelation."

specializations of performers and the relative importance of research topics that affect both subcommittee actions and NIH awards. The following section hence exploits a database of all NIH peer-reviewed grants to test whether research performers represented by members of the LHHE subcommittees receive increased funding, after controlling for various unobservable characteristics of these research performers. The near absence of performer-specific earmarks and abundance of field-specific transfers suggest that any observed concentration of NIH funds in the constituencies of members must be a consequence of the indirect transfers achieved by the language of subcommittee reports.

2.3 Empirical specification and data

2.3.1 Empirical specification

To test the influence of appropriations committee members on the level of peer-reviewed funds for biomedical R&D received by performers, I estimate a linear regression of the form:

$$\log(\text{GRANT})_{ijt} = \alpha + \beta \text{REP}_{jt} + \delta T_t + C_i + u_{ijt} \quad (1)$$

where i indexes the research institution or performer receiving NIH grants, j the state of the research performer's location, and t the time period of the grant. The dependent variable is a logged measure of NIH research grant dollars. REP is the number of committee members in the state of the research performer. I separately estimate the influence of LHHE subcommittee members and other members of appropriations committees since the latter may trade constituency benefits with LHHE members (Weingast and Marshall 1988).

Unobserved factors that affect allocations to performers, such as the growth during this period of overall federal funding for biomedical R&D, may be correlated with performers' representation in appropriations committees (Figure 1 and Table 2 respectively show that both NIH grants and the number of members on the LHHE subcommittees have grown during the period of this study). To eliminate the possibility of spuriously inferring a relationship between performer receipts of NIH grants and representation simply because the two variables display similar time trends, I include T to capture trends in NIH grants common across all grant recipients.

Research performer effects C_i control for the unobserved characteristics of performers – such as their research quality, size of research enterprise, or research specialization – that may be correlated with both their receipts of research grants and representation in committee positions. Since performers do not change their location, C_i also captures the time-constant unobservable attributes of the districts and states of performers' location.

2.3.2 The data

(i) *Biomedical research funds*

The Consolidated Grant Applicant File (CGAF) database contains a record of every research proposal for which a grant was made by the “dual peer review” process at the NIH. After eliminating awards that supported “intramural” activities (*i.e.* research performed at federal labs and the NIH) and research in non-U.S. locales, I identified 8,310 unique institutional recipients (based on the institutional affiliation of the primary investigator) of NIH grants between the years 1984 through 2003.⁴⁵ For each of these 20 years, I gathered the annual dollar amount of awards received by these 8,310 research performers. These awards represent about 70%⁴⁶ of all federally supported biomedical R&D and 95%⁴⁷ of the NIH’s total extramural grants for the period. Figure 2.1 incorporates these data in a graph of the total dollar value of the awards made by the NIH for the years 1984-2003.

NIH grant recipients are classified as public universities, small firms (for-profit entities with fewer than 500 employees), private universities, corporations (for-profit entities with more than 500 employees), and others (including non profits, hospitals, and community colleges). Public universities are the largest recipients of NIH funds – in 2003, public universities received 41.5% of all NIH extramural support awarded to U.S. performers, followed by private universities (34.6%) and other nonprofit institutions (20.5%). Figure 2.2 displays trends in NIH funding for each of the five major categories of R&D performers during 1984-2003.

(ii) *Congressional Appropriations Committee membership*

I collected HAC and SAC membership data from Congressional directories. The HAC assigns its members to 12 subcommittees, each of which is in charge of drafting appropriations bills for specific federal agencies and programs. The SAC also has 12 subcommittees, and each member of the SAC typically sits on six to seven subcommittees, unlike her average House counterpart who sits on a maximum of three subcommittees. As noted earlier, LHHE is the subcommittee responsible for NIH’s appropriations. Table 2.2 reports the number of appropriations committee members, LHHE subcommittee numbers, and the corresponding number of unique states represented for the period of this study (98th through 107th Congress or 1983 through 2002). The median HAC had 57 members, 13 of whom were assigned to the LHHE subcommittee and the median SAC had 29 members, 15 of whom sat on the corresponding LHHE.

Tables 2.3A and 2.3B report patterns of membership for the represented states in the House and Senate LHHE subcommittees. Representation is affected by members’ entries and exits from the subcommittee, and a significant number of states are not represented (30 of the 51 states were never represented in the House LHHE and 23 states never had Senators on that chamber’s LHHE during this period), generating between- and within- variation in the dependent variable. I collected information on the subcommittee positions of each

⁴⁵ This starting point was dictated by the availability of subcommittee membership data. Congressional directories prior to 1983 report appropriations committee members, but omit their subcommittee assignments (except for subcommittee chair and minority ranking member).

⁴⁶ The numerator excludes intramural, foreign and performers for which institution identity, address or grant amount could not be determined.

⁴⁷ The numerator excludes performers for which institution identity, address or grant amount could not be determined.

chamber's LHHE subcommittee members (chairmanship, ranking minority membership and rank) and party status (majority or minority).⁴⁸

Next, I identify the states (and Congressional districts) in which research performers are located from their addresses (inferred from their ZIP codes) by using the U.S. Census' "Congressional District Geographic Relationship Table." Finally, I match the appropriations committee data for each two-year Congress to the corresponding funding allocations of that Congress's two NIH appropriations bills. The House and Senate Appropriations Committee composition data for the 107th Congress (years 2001 and 2002) for example, are matched to the NIH grants made during the years 2002 and 2003 (the i in (1) thus indexes successive congressional years rather than calendar years). Arranged in this manner, each row of the data contains the funds received by a research performer i during the congressional year i , and the corresponding representation information for the performer's state for the Congress. The mean institution-year pair in my data receives \$ 6,850,247 in NIH grants (SD = \$ 3.5e+07).

2.4 Results

2.4.1 Committee member influence

Table 2.4 presents pooled least squares estimates of the effect of LHHE and other HAC and SAC members on the peer-reviewed biomedical R&D funds received by research performers. Since the dependent variable contains logged values of strictly positive dollar amounts, the coefficients represent effects conditioned on the receipt of R&D funds by performers. All statistical tests are based on White's heteroskedasticity corrected standard errors.

The first and second columns respectively report estimates of returns to committee membership without and with controls for the characteristics of research performers. Because estimates of β in specifications with performer fixed effects are significantly positive, and those from specifications without fixed effects are statistically indistinct from zero, the unobservable attributes of grant recipients (such as their quality or quantity in represented states) appear to be negatively correlated with representation.

Column 2 suggests that each HAC-LHHE subcommittee member is associated with a 5.3% increase in biomedical research funds for the represented institution ($p < 0.004$). Representation on the SAC-LHHE subcommittee membership yields no significant increase in R&D funds for performers, but non-LHHE representation in the SAC results in an average increase in funding for represented institutions of 5.3% ($p < 0.021$). To investigate this surprising finding, I estimated the impact of excluding individual Senators on the SAC non-LHHE coefficient. This analysis revealed that (nearly) all of the effect of SAC non-LHHE members reported in Column 2 (of Table 2.4) can be attributed to New York Senator Alfonso D'Amato, a member of various non-LHHE subcommittees of the SAC

⁴⁸ For these data, I thank Charles Stewart III

through 1994 during the period of this study.⁴⁹ Column 3 (of Table 2.4) separates the effect of D’Amato (by using a dummy variable to indicate the Senator’s state and tenure) and shows that the effect of other non-LHHE SAC members is not statistically different from zero. This “final” specification estimates the returns to performers per HAC-LHHE member as 5.9% ($p < 0.001$).^{50, 51} A 5.9% increase in funding for the mean R&D performer translates into an average increase of \$370,000 per congressional year. These findings of the disproportionate influence of House LHHE members is consistent with the characterization by Congressional scholars of HAC members as more specialized (and influential) in the activities of their subcommittees than SAC members. The smaller size of the Senate may also enable individual Senators like D’Amato to exercise influence over matters outside the jurisdiction of their SAC subcommittees (cf. Fenno 1966, Savage 1999).

The aggregate premium enjoyed by research performers represented on the HAC-LHHE, along with that enjoyed by performers in New York during Senator D’Amato’s period in office, can be calculated from (1) by: $\sum_{ij} GRANT_{ij} \times \hat{\beta}_j \times REP_{ij}$ where $\hat{\beta}_j$ are the estimated coefficients of representation. Table 2.5 uses the estimates reported in the last column of Table 4 (significant at $p < 0.001$) to calculate the amount of additional funds received by institutions due to committee membership. The allocation of \$1.7 billion of the \$37 billion awarded by the NIH in 2002 and 2003 appears to reflect the influence of appropriations committee members. Since House LHHE members account for more than 70% of the overall significant effects of representation, the rest of this analysis focuses on their influence while controlling for the effects of all other committee positions.

2.4.2 Robustness checks and alternative explanations

If the relative demand of research performers for NIH grants changed during years 1983-2002, and if performers successfully lobby to be assigned subcommittee positions in response to their changing demands, then time-constant performer intercepts may not adequately control for the endogeneity of LHHE entry and NIH grants. To investigate this possibility, I examined the effect of entry and exit by members from the House LHHE

⁴⁹ Senator D’Amato earned the nickname “Senator Pothole” for his delivery of constituency services (The New York Times 1992).

⁵⁰ The specifications in Table 2.4 impose the effect of a second representative from a state to be the same as that of the first. I tested whether a second HAC-LHHE representative from a state has the same effect as the first by estimating model (1) with dummy variables for one and two representatives. This yielded a coefficient estimate of 0.109 on the variable indicating two HAC-LHHE representatives (which is nearly twice the estimate of 0.059 per HAC LHHE member reported in Table 4) and an estimate of 0.001 on single HAC-LHHE representation. However, these coefficients were estimated with large standard errors (0.036 and 0.031 respectively compared to 0.018 on the coefficient of HAC LHHE of Table 2.4) and the (95%) confidence interval for the single HAC-LHHE dummy did not exclude the estimate obtained on the HAC-LHHE count variable. The following estimations hence retain HAC-LHHE as a count variable.

⁵¹ States represented in the chair of the HAC-LHHE receive 9.1% more in NIH grants, but this effect is estimated with a S.E. of 0.07 and does not statistically reject the null effect. Minority party members of the HAC-LHHE appear to be associated with higher returns (7.6%) than majority members (3.4%) but I was unable to reject the equality of the majority and minority coefficients by a Wald test ($Pr > F = 0.20$). Performers in states representing party leaders do not appear to receive increases beyond the effects attributed to appropriations committee members.

subcommittee in a panel of research performers that were represented on the subcommittee at least once during 1983-2002. This yielded a dataset of 5,930 research performers in 20 states. Results are reported in Table 2.6.

Table 2.6 shows that performers that were represented at least once during years 1983-2002, experienced a 6% increase in NIH funds during the years of representation. This estimate represents a significant (at $p < 0.01$) increase from “before-representation” performer-years, the excluded reference group. In years following the exit of their representative from HAC-LHHE, these performers received no more or less funding than in the years prior to their representation. Because subcommittee member exits are exogenous events (in my panel, six of the nine exits were due to death or retirement from public life of the member) and unlikely to be correlated with the changing specializations of research performers, these results on increased funding for performers only during the years in which they are represented, strengthen a causal interpretation of committee member influence on NIH funding for represented institutions.

Second, although the most salient definition of “constituency” for House members’ efforts to channel resources to their supporters is the congressional district, the regression equations define representation of House members at the state level. I redefined the relevant “locality” for purposes of analyzing NIH grants as the congressional district in an alternative specification and found that the effects of House subcommittee membership are estimated as 6.2% ($p < 0.001$) at the state level and 2.7% (statistically not different from zero) at the congressional district level. One explanation for this result is that fewer than 4% of NIH grant recipients overall are located in the districts of subcommittee representatives and 83% of the represented recipients are in the states but not the Congressional districts of House LHHE members.⁵² Considering representation by state increases variation in the dependent variable and ensures comparability of House and Senate effects without inducing known biases in my estimates.⁵³

Third, one could argue that represented research performers receive additional peer-reviewed grants not because of field level transfers made by LHHE members, but through their use of alternative channels of political influence. For example, bureaucrats at the NIH may award peer-reviewed grants to performers in the constituencies of members in exchange for rewards like promotions or higher appropriations from their political principals. This explanation is hard to reconcile with NIH’s consistent receipts of appropriations in excess of the amounts requested in the President’s budget. In addition, if LHHE members’ distributive preferences are satisfied by NIH bureaucrats outside the formal appropriations

⁵² House members may be influenced by Senatorial ambitions and therefore work to attract federal benefits to their home states. Also, individual states are limited in the number of members that may be seated on any appropriations subcommittee, which might further broaden the relevant locus for indirect transfers of federal benefits to the state from the district level (Bullock 1971).

⁵³ I also estimated various alternative specifications of the model in (1). A specification that clustered standard errors by interacting state and congressional years (since there are multiple performers per state and representation does not vary by state-year) estimated the HAC-LHHE effect as 6.2% ($p < 0.007$). A regression that included year dummies instead of the trend variable estimated the HAC-LHHE effect as 4.6% ($p < 0.01$). A specification that included lagged year funding receipts by the research performer on the RHS estimated the LHHE effect as 6.2% ($p < 0.001$). These alternative estimates are not statistically different from the “final” estimates reported in the last column of Table 4.

process, then we should not observe funding reallocations in appropriations bills and meeting reports.

2.4.3 Additional results

Do some research performers benefit more than others from committee representation? Public universities represent the single largest category of recipients (refer Figure 2) of NIH support and many of these institutions have a long history of R&D activity that seeks to generate benefits for the local economy (Rosenberg & Nelson 1994). State-level politicians influence the operations of state universities and may lobby on their behalf for federal benefits (Sabloff 1997). A second class of NIH grant recipients that may benefit from representation is single-location small business firms which may be more effective political supporters within a state than branch plants of larger counterparts. Table 2.7 reports the effects of committee representation on NIH grants to different R&D-performer categories. An additional HAC-LHHE member increases NIH grants to public universities in the member's state by 8.8% and grants to small businesses by 10.3%. Neither public universities nor small businesses benefit from having a representative on the full HAC. Senator Alfonso D'Amato's representation on the SAC appears to have primarily benefitted private universities and other nonprofits (foundations, laboratories, independent hospitals and other health and community organizations), reflecting New York State's abundant endowment of private research universities and nonprofits.

The NIH awards various types of peer-reviewed grants depending on the type of project and performer. "R-type" grants fund the research projects of individual investigators and comprise about 60% of NIH's total extramural awards. "P-type" grants fund research programs and centers and comprise 17-20% of NIH's total awards. Estimations on these and other types of awards do not suggest that political representatives systematically influence the concentration of any one type of award over the other.^{54,55}

2.5 Political influence and the concentration of federal research funds

The tension between the distributional consequences of the peer review process and those associated with a system more obviously subject to political influence was a key element in the political conflict between Vannevar Bush, former director of the Office of Scientific Research and Development during World War II, and West Virginia Senator Harley Kilgore over Bush's proposal for a "National Research Foundation" in 1945. Bush proposed a politically insulated system that was self-regulated by scientists for the distribution of federal research funds. Kilgore argued that such a system would result in the concentration of funds at a few elite institutions and advocated more political control to ensure an equitable geographic distribution of public research resources (Kleinman 1995).⁵⁶ Echoing this debate, some recent science policy scholars argue that politically mandated earmarks increase

⁵⁴ R-type awards are further classified as R01, R02,..R29 and P-type awards as P01,..P07, P09, P11, etc.

⁵⁵ The returns on each HAC LHHE members is estimated as 4.4% ($p < 0.01$) for R-type grants, but the C.I.s around the positive effect of these representatives on the other types of grants fails to exclude zero.

⁵⁶ The debate significantly altered Bush's proposal and delayed the creation of what is now the National Science Foundation until 1953.

the breadth and number of competitive R&D performers (see for *e.g.* Silber 2002), while others contend that political influence in the allocation of R&D resources shifts funds towards “less deserving” research performers (Savage 1999).⁵⁷

The above assertions notwithstanding, the distributional effects of peer review and political control have rarely been tested and remain ambiguous. Here, I test the extent to which an institution’s historical strength in research fields mediates the influence of subcommittee members on its NIH funding by using R&D performers’ grants from individual NIH Institutes as a proxy for performers’ expertise in specific research fields. The empirical model in (1) is extended as follows:

$$\begin{aligned} \log(GRANT)_{ijkt} = & \alpha + \beta REP_{jt} + \delta QUARTILE_{ijkt-1} + \theta(REP_{jt} * QUARTILE_{ijkt-1}) \\ & + \chi T_t + C_i + D_k + u_{ijkt} \end{aligned} \quad (2)$$

where ‘*i*’ indexes the research performer, ‘*j*’ the state, and ‘*t*’ the years of grant receipts as before. ‘*k*’ represents the biomedical research field (based on the NIH Institute responsible for the grants). The dependent variable is a logged measure of the research funding received by performer ‘*i*’ in field ‘*k*’ and year ‘*t*.’ *REP* is the number of HAC members. *QUARTILE* is a variable that proxies for a performer’s relative expertise in a particular biomedical field, based on the performer’s share of previous funding from a given Institute.⁵⁸

QUARTILE is a vector of four binary variables indicating the quartile placement for each performer–field–congressional year observation.⁵⁹ Placement in higher quartiles represents larger receipts. For example: the Fred Hutchinson Cancer Research Center and Louisiana State University A&M College at Baton Rouge are among the top recipients of NCI grants in the years 2000-01 and based on this, are placed in quartile 4 (the highest quartile) for 2002-03. However, LSU is assigned to quartile 2 for “heart and lung-related R&D,” based on its funding from the NHLBI for 2000-2001.

The right hand side includes variables that capture trends in NIH grants that are common across all recipients. Research performer effects ‘*C_i*’ control for time-constant performer- and state-level characteristics related to representation, as was discussed in a previous

⁵⁷ Chubin and Hackett (1990) offer an alternative explanation for the link between peer review and concentration: peer reviewers are more likely to view research proposals from long-standing and reputed recipients as safe bets. Also, peer reviewers are either drawn from established research institutions, or are friends with researchers affiliated to established institutions, and favor members of this “old boys network.” Hence peer review leads to “the narrow channeling of an excessive percentage of federal research support to only a handful of established universities” (Silber 2003, p 108).

⁵⁸ Rather than drop observations for 1983-1984 because of the non-availability of lagged variables, I used funding data from 1981-82 to construct the quality variable for the corresponding records.

⁵⁹ A chief advantage of the proxy for research expertise based on the lagged receipt of field-level funding for performers is that it captures field-level differences in expertise within research institutions for the performers in my sample. External measures of research expertise like the National Research Council’s departmental ratings are available only for a limited number of research performers (fewer than 900 of the 8310 performers in my data), departments and years during the period of my study. One criticism of the proxy could be that since current funding levels are predicted by a measure based on previous funds, the estimates are susceptible to serial correlation in the error term. However, current funding levels are predicted here by previous year funding shares captured by quartiles that tend to be stable across time.

section. Intercepts for the different institutes at the NIH ‘ D_k ’ hold constant unobserved research field-specific attributes such as the health burden or importance of biomedical research fields that influence grant receipts and LHHE membership.

Table 2.8 shows that biomedical fields in the represented research performers are not randomly chosen by committee members for support; research performers that are in the bottom quartiles for a given field, average increases in NIH funding of 3.6% (for first-quartile institutions) and 6.4% (second-quartile institutions).⁶⁰ Political representation appears to have little incremental effect on NIH grant awards to institutions that rank relatively high in specific fields.

2.6 Concluding remarks

Politicians use their power over the federal purse to transfer public resources to special interest groups. In the case of biomedical R&D, Congressional appropriators allocate federal funds to specific research fields and projects. These transfers could be motivated by the public interest, appeasement of disease-specific lobbying groups, or the concentration of benefits in members’ states. Although all of these motives assuredly play some role, I have here argued that a significant factor in the support of specific research fields by committee members is the transfer of funds to research performers in their states. Representatives prefer to rely on indirect methods to transfer these public resources, rather than earmark funds for particular performers, to avoid any appearance of interference with a system renowned for rewarding the scientific excellence of performers.

I find that research performers from states with members on the HAC-LHHE subcommittee receive 5.9 – 10.3% more NIH peer-reviewed funds. These estimates, drawn from a period during which the total NIH budget grew from \$8.4 billion in 1984 to \$30.2 billion (Constant FY2008 dollars) in 2003, are comparable in magnitude to estimates of political influence in the allocation of military contracts during the Cold War era (Rundquist *et al* 1996), and to the findings of Ferejohn’s study on political influence in the allocation of federal funds for rivers and harbors projects. I estimate that representation on the relevant committee or subcommittee influenced the allocation of 5.3% of the NIH’s overall extramural R&D awards during the period of this study. In the year 2003 alone, this amounted to \$0.9 billion – about half the value of all federal performer-specific earmarks identified by the *Chronicle of Higher Education* for that year.

What are the implications of my findings for the “efficiency” of the public biomedical R&D system in the U.S.? The answer depends on the extent to which political influence distorts the structure of allocations implied by a socially optimal funding criterion. If we define an optimal rule as one that allocates funds based on the scientific opportunity and societal burden associated with different diseases, then any intervention that results in a different

⁶⁰ The modal lagged year funding for fields in the first quartile was \$0, suggesting that political benefits are maximized for fields in which performers have some research presence (*i.e.* fields in the 2nd quartile).

pattern of allocations will be inefficient.⁶¹ If, on the other hand, the allocation of public R&D resources is constrained to be a “second best” process, reflecting uncertainties regarding the benefits of ameliorating different diseases, then subcommittee members may have a role in resolving uncertainty by advocating funding for research in specific disease areas (Gilligan & Krehbiel 1990). My findings however, on the location of beneficiaries and inferior nature of R&D projects supported by political representatives are inconsistent with a purely informational perspective of the role of subcommittee members.

⁶¹ Scientific opportunity and disease burden (public health need) are stated by NIH officials as the two main inputs to decisions regarding the allocation of funds for research in different diseases (McGeary & Smith 2002).

Chapter 2 Figures and Tables

FIGURE 2.1: TOTAL NIH EXTRAMURAL GRANTS (Y1984-2003)

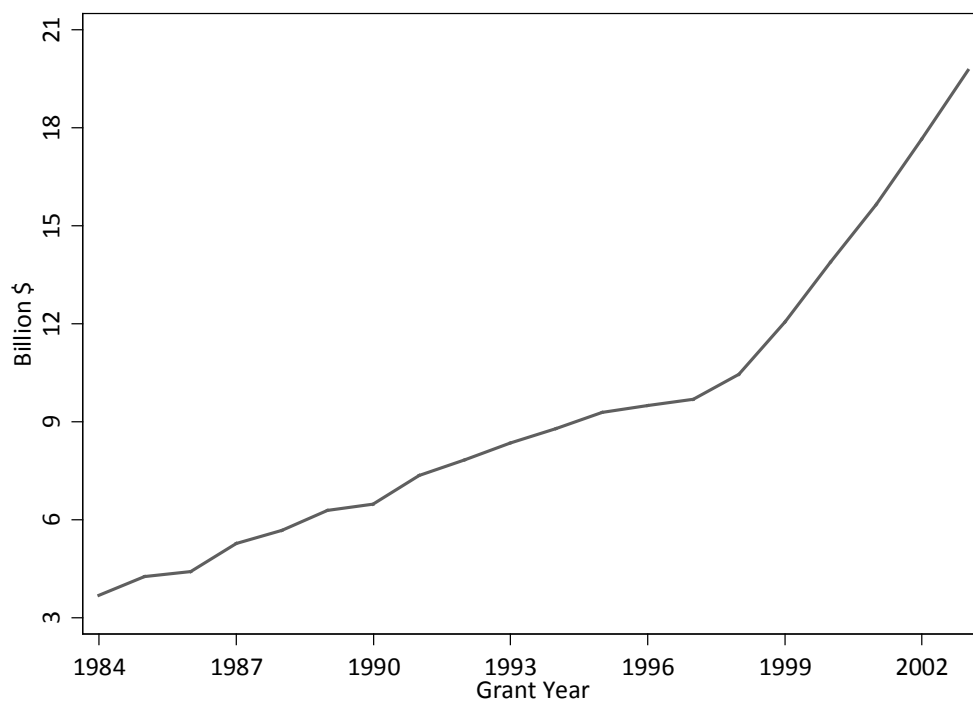


FIGURE 2.1 NOTES: Figure 2.1 plots NIH grants during the years 1984-03 for extramural research performers. Source: author calculations from Consolidated Grant Application File (CGAF).

FIGURE 2.2: NIH EXTRAMURAL GRANTS BY PERFORMER TYPE (Y1984-2003)

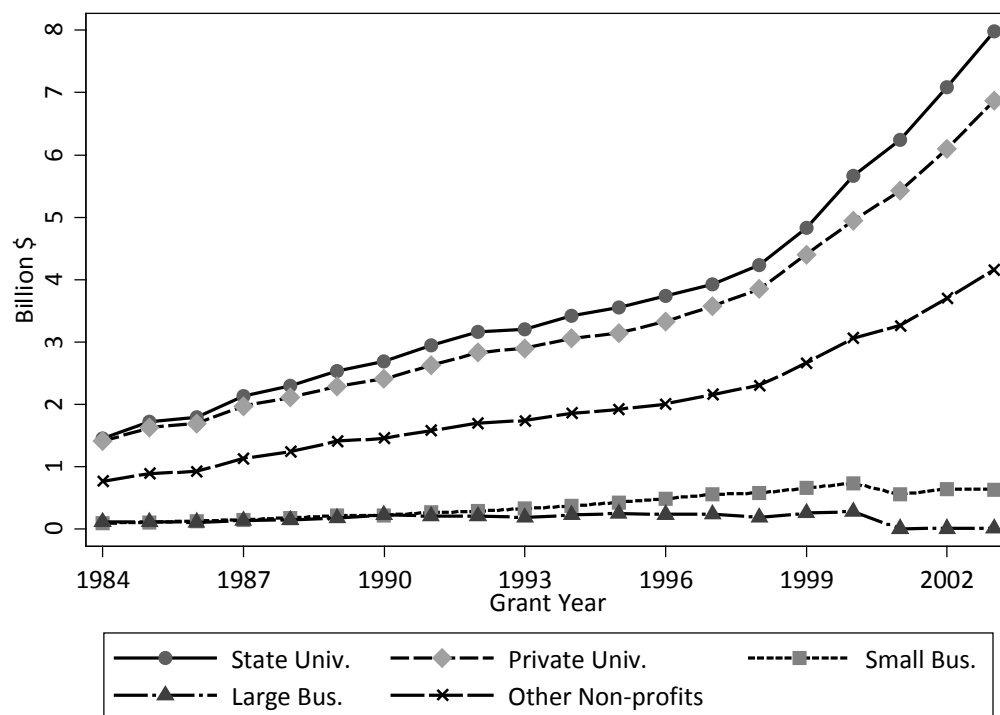


FIGURE 2.2 NOTES: This Figure plots NIH grants for different extramural research performer types during the years 1984-03. Source: author calculations from Consolidated Grant Application File (CGAF).

TABLE 2.1: INSTITUTES AND CENTERS AT THE NATIONAL INSTITUTES OF HEALTH

Institute/Center	Est. Year	Grants B\$ (1984-2003)
National Cancer Institute (NCI)	1937	326.34
National Heart, Lung, & Blood Institute (NHLBI)	1948	236.39
National Institute of Allergy & Infectious Diseases (NIAID)	1948	183.32
National Institute of General Medical Sciences (NIGMS)	1962	178.55
National Institute of Diabetes & Digestive & Kidney Diseases (NIDDK)	1948	132.76
National Institute of Neurological Disorders & Stroke (NINDS)	1950	114.52
National Institute of Mental Health (NIMH)	1949	97.78
National Institute of Child Health & Human Development (NICHD)	1962	94.30
National Center for Research Resources (NCRR)	1962	89.48
National Institute on Aging (NIA)	1974	69.10
National Institute on Drug Abuse (NIDA)	1973	66.45
National Eye Institute (NEI)	1968	53.40
National Institute of Environmental Health Sciences (NIEHS)	1969	45.21
National Institute of Arthritis & Musculoskeletal & Skin Diseases (NIAMS)	1989	38.63
National Institute on Alcohol Abuse & Alcoholism (NIAAA)	1970	31.08
National Institute of Dental & Craniofacial Research (NIDCR)	1948	26.84
National Institute on Deafness & Other Communication Disorders (NIDCD)	1988	25.90
National Human Genome Research Institute (NHGRI)	1989	24.67
National Institute of Biomedical Imaging & Bioengineering (NIBIB)	2000	3.53
<i>Others including:</i>		32.60
National Institute of Nursing Research (NINR)	1986	
National Library of Medicine (NLM)	1956	
Center for Information Technology (CIT)	1964	
Center for Scientific Review (CSR)	1946	
John E. Fogarty International Center (FIC)	1968	
National Center for Complementary & Alternative Medicine (NCCAM)	1999	
National Center on Minority Health & Health Disparities (NCMHD)	1993	
NIH Clinical Center (CC)	1953	

TABLE 2.1 NOTES: The Table lists the 20 institutes and 7 centers at the National Institutes of Health, and the years during which each was established. The third column lists the total amount of grants made by each institute/center during the years of my study (grant years 1984 through 2003 or appropriation years 1982 through 2002). The category “Others” combines the allocations of the smaller (by R&D grant \$) institutes/centers at the NIH. Source: Information in the first two columns were gathered from the NIH’s website (<http://www.nih.gov/icd/>) and figures in the last column represent author calculations from the Consolidated Grant Application File (CGAF).

TABLE 2.3B: STATES REPRESENTED IN THE SENATE LHHE SUBCOMMITTEE
(98th – 107th CONGRESS)

STATE NAME	1983	1985	1987	1989	1991	1993	1995	1997	1999	2001
ALASKA	1	1	1	1	1	1			1	1
ARIZONA									1	
ARKANSAS			1	1	1	1	1	1		
CALIFORNIA									1	
CONNECTICUT	1*	1*	1							
FLORIDA	1	1	1*			1	1			
HAWAII	1	1	1	1	1	1	1	1	1	1
IDAHO	1	1	1	1				1	1	1
IOWA		1	1	1	1*	1*	1	1	1	1*
LOUISIANA										1
MISSISSIPPI				1	1	1	1	1	1	1
MISSOURI	1						1	1		
NEVADA				1	1	1	1	1	1	1
NEW HAMPSHIRE	1	1	1	1	1		1	1	1	1
NEW MEXICO	1	1	1							
NORTH CAROLINA								1		
NORTH DAKOTA	2	2	1	1	1					
OHIO										1
OREGON	1	1	1	1		1	1			
PENNSYLVANIA	1	1	1	1*	1	1	1*	1*	1*	1
SOUTH CAROLINA	1	1	1	1	1	1	1	1	1	1
TEXAS				1	1			1	1	1
VERMONT							1			
WASHINGTON				1	2	2	1	2	2	1
WEST VIRGINIA	1	1	1	1	1	1	1			1
WISCONSIN	1	1	1			1	1	1	1	1

TABLE 2.3 NOTES: Tables 2.3A & 2.3B respectively list the states represented in the LHHE subcommittee of the House and Senate appropriations committees, and the number of representatives from these states on the subcommittees for the 10 Congressional years between 1983 and 2002. * indicates Senate LHHE subcommittee chair. Source: Congressional Directories.

TABLE 2.4: LEAST SQUARES REGRESSION ESTIMATES OF RETURNS TO
HOUSE & SENATE COMMITTEE REPRESENTATION
(98th – 107th CONGRESS OR 1984-2003)

dependent variable = log of Total NIH grant \$			
	1	2	3
HAC LHHE members	0.005 [0.020]	0.053 [0.018]**	0.059 [0.018]**
Other HAC members	0.016 [0.008]	0.024 [0.013]	0.027 [0.013]*
SAC LHHE members	0.003 [0.032]	-0.002 [0.030]	-0.024 [0.031]
Other SAC members	-0.026 [0.030]	0.053 [0.023]*	0.009 [0.025]
Al D'Amato			0.25 [0.063]**
trend	0.077 [0.005]**	0.14 [0.004]**	0.144 [0.004]**
Constant	12.605 [0.035]**	12.166 [0.038]**	12.138 [0.039]**
Research performer FE	N	Y	Y
N of performers	8310	8310	8310
Observations	24492	24492	24492
R-squared	0.01	0.88	0.88
Robust standard errors in brackets			
* significant at 5%; ** significant at 1%			

TABLE 2.4 NOTES: This Table reports estimates from Least Squares regressions of the logged R&D dollars received by research performer-years (1 Congressional year = 2 grant years) on the number of representatives in the research performer's states for the various appropriations committee offices. Column 1 reports estimates of House & Senate representation without performer-fixed effects and Columns 2 & 3 with performer-fixed effects. Column 3 estimates separately the effect of Senator Alfonso D' Amato (NY state, Other SAC member b/w 1984-1994 in the dataset).

TABLE 2.5: ESTIMATES OF HOUSE & SENATE COMMITTEE
 REPRESENTATION EFFECTS IN BILLION \$
 (98th – 107th CONGRESS OR 1984-2003)

Congress year	HAC-LHHE effect (B\$)	Al D'Amato effect (B\$)	Total political effect (B\$)	Total allocations(B \$)	Political effect as% of Total
1983-84	0.29	0.28	0.57	8.46	6.74
1985-86	0.35	0.33	0.68	10.45	6.50
1987-88	0.43	0.39	0.81	12.80	6.33
1989-90	0.49	0.42	0.91	14.95	6.09
1991-92	0.55	0.46	1.01	16.81	6.01
1993-94	0.7	0.48	1.18	18.73	6.30
1995-96	0.74	0	0.74	20.43	3.62
1997-98	0.69	0	0.69	24.24	2.85
1999-00	1.13	0	1.13	30.44	3.71
2001-02	1.66	0	1.66	37.35	4.44

TABLE 2.5 NOTES: Table 2.5 uses the statistically significant (at 99% or above CI) estimates of appropriations committee representatives on the receipts of represented research performers (from Column 4 of Table 2.4) to calculate the additional amounts received by represented institutions due to committee members (SAC, Non-LHHE member representing New York State from 1984-1994 in my dataset). The first column computes the amounts due to HAC-LHHE representation (5.9%) and the second due to Senator Al D'Amato's tenure (25%). The third column sums these two effects.

TABLE 2.6: POOLED LEAST SQUARES ESTIMATES OF RETURNS TO HOUSE COMMITTEE REPRESENTATION ON ENTRY & EXIT OF MEMBERS
(98th – 107th CONGRESS OR 1984-2003)

dependent variable = log of Total NIH grant \$		
	All	Represented only
HAC LHHE members	0.059 [0.018]**	
Current HAC LHHE members		0.06 [0.024]*
Post HAC LHHE members		-0.002 [0.057]
Other HAC members	0.027 [0.013]*	0.032 [0.015]*
SAC LHHE members	-0.024 [0.031]	0.012 [0.040]
Other SAC members	0.009 [0.025]	0.039 [0.031]
Al D'Amato	0.25 [0.063]**	0.211 [0.069]**
trend	0.144 [0.004]**	0.142 [0.005]**
Constant	12.138 [0.039]**	12.113 [0.055]**
Research performer FE	Y	Y
N of performers	8310	5930
Observations	24492	17487
R-squared	0.88	0.88
Robust standard errors in brackets		
* significant at 5%; ** significant at 1%		

TABLE 2.6 NOTES: Table 2.6 reports estimates from OLS regressions of the logged R&D dollars received by research performer-years (1 Congressional year or 2 grant years) on the status of representatives in the research performer's states for the House appropriations committee offices. Column 2 utilizes observations from states that were at least once represented in the House LHHE subcommittee during the period of my study. For these institutions, the estimates present the effect of members before (base group which is omitted), during, and after representation on research performers. Column 1 reproduces for comparison, estimates from Column 4 of Table 2.4.

TABLE 2.7: POOLED LEAST SQUARES ESTIMATES OF RETURNS TO COMMITTEE REPRESENTATION BY RESEARCH PERFORMER TYPE (98th – 107th CONGRESS OR 1984-2003)

dependent variable = log of Total NIH grant \$					
	Public U.	Private U.	Small B.	Large B.	Nonprofits
HAC LHHE members	0.088 [0.032]**	0.02 [0.033]	0.103 [0.034]**	-0.233 [0.263]	0.031 [0.030]
Other HAC members	0.018 [0.019]	0.044 [0.023]	0.012 [0.026]	0.202 [0.219]	0.01 [0.023]
SAC LHHE members	0.046 [0.042]	-0.066 [0.077]	-0.099 [0.060]	0.043 [0.488]	0.008 [0.053]
Other SAC members	-0.015 [0.034]	-0.057 [0.058]	-0.007 [0.050]	0.519 [0.298]	0.041 [0.049]
Al D'Amato	0.185 [0.104]	0.322 [0.125]*	-0.004 [0.153]	-0.175 [0.604]	0.25 [0.099]*
trend	0.15 [0.005]**	0.103 [0.007]**	0.193 [0.009]**	-0.096 [0.056]	0.13 [0.007]**
Constant	13.841 [0.044]**	13.251 [0.077]**	11.049 [0.088]**	13.569 [0.488]**	12.594 [0.072]**
Research performer FE	Y	Y	Y	Y	Y
N of performers	438	433	5311	175	1953
Observations	2963	2210	12050	517	6752
R-squared	0.94	0.95	0.71	0.75	0.88
Robust standard errors in brackets					
* significant at 5%; ** significant at 1%					

TABLE 2.7 NOTES: The Table reports estimates from Pooled Least Squares regressions of the logged R&D dollars received by research performer-years on the number of representatives in the research performer's states for various appropriations committee offices. Each column reports the effects of representation on the type of research performer indicated in the column headers.

TABLE 2.8: RETURNS TO HOUSE COMMITTEE REPRESENTATION BY QUALITY OF RESEARCH FIELD (98th – 107th CONGRESS)

dependent variable = log of Total NIH grant \$	
HAC LHHE X QUARTILE1	0.036 [0.016]*
HAC LHHE X QUARTILE2	0.064 [0.015]**
HAC LHHE X QUARTILE3	-0.002 [0.013]
HAC LHHE X QUARTILE4	-0.004 [0.012]
QUARTILE2	0.286 [0.016]**
QUARTILE3	0.904 [0.017]**
QUARTILE4	2.335 [0.019]**
OTHER HAC MEMBERS	0.013 [0.006]*
SAC LHHE members	0.003 [0.015]
Other SAC members	-0.002 [0.013]
Al D'Amato	0.096 [0.031]**
TREND	0.103 [0.002]**
Constant	12.037
PERFORMER FE	Y (8310)
INSTITUTE FE	Y (20)
Observations	70706
R-squared	0.77
* significant at 5%; ** at 1%	

TABLE 2.8 NOTES: This table reports estimates from OLS regressions of the logged R&D dollars received by research performer-biomedical field-years (1 Congressional year or 2 grant years) on the number of LHHE and other appropriations committee representatives in the research performer's states. Quartiles are based on lagged receipts of R&D dollars received by the research performer in the biomedical field. Quartile-1 represents the lowest recipient group (omitted base group) and Quartile-4 the highest. The coefficients on the interaction terms of the four quartiles with HAC LHHE membership capture the relationship between historical strength of fields of performers and effects of representation.

Chapter 3

Pioneering inventors or thicket-builders: which U.S. firms use continuations in patenting?

3.1 Introduction

A large literature spanning economics, law, and management has considered the strategic uses by firms of patents and the effects of these strategies on innovation. This literature has highlighted firms' decisions to acquire patents in fields in which company executives state that patents are of little use in appropriating the returns to innovation (Hall & Ziedonis 2001), the role of patents in technology licensing negotiations (Lamoreaux & Sokoloff 1999, Arora *et al.* 2001), and the interaction between patent strategy and litigation risk (see Hall & Ziedonis 2007, as well as Somaya 2003). The use by firms of patent prosecution procedures, however, has received less attention from scholars, despite acknowledgement by patent attorneys and others of the importance of procedural strategies in firms' management of intellectual property. This study investigates the strategic use of the patent prosecution process by inventors at the United States Patent and Trademark Office (USPTO) in an analysis of U.S. corporate assignees' decisions to file continuation applications.

Continuation applications permit firms to restart the examination of their patent applications while retaining the filing date of a previous application that discloses the same invention. Inventors can use continuations to revise the claims submitted in their initial application or to pursue claims that have been disallowed after initial examination with new arguments and evidence. According to some corporate IP managers and patent attorneys, continuations are filed by "pioneering inventors" to "obtain adequate protection of inventions that often take a relatively long time to reach the marketplace" (see for example, comments by the Biotechnology Industry Organization, 2006). In this view, inventors use continuations to modify the claims in their patent applications to reflect developments in their inventions that occur after they have filed a patent application.

A very different characterization of the use of continuations argues that patentees file continuing applications to acquire patents with weak claims of dubious quality that were rejected by the examiner during initial prosecution (see Quillen & Webster 2001). These lower-quality patents can be valuable to patentholders seeking to accumulate a thicket of patents for "defensive" purposes and/or to improve their bargaining position in patent cross-licensing negotiations (Shapiro 2001). Additionally, according to Lemley & Moore

(2004), inventors may use the continuations procedure to increase uncertainty for rivals' R&D investment decisions, or to acquire so-called "submarine patents."^{62, 63}

The continuations procedure is unique to the U.S. patent system and introduces significant delay in the prosecution process: for patents issuing from applications with continuations, the median grant lag (the time between an initial patent application and its final grant) is 44 months, substantially exceeding the median prosecution time of 23 months for patents that are not continued.⁶⁴ The procedure is used by a significant number of patent applicants – 29% of the nearly one million patents applied for between 1981 and 2000 and granted to U.S. firms during 1981-2004 are from continuing applications, and the procedure imposes a significant burden on USPTO resources.⁶⁵ Whether continuations are filed by firms to protect their pioneering inventions, or as part of defensive patenting strategies that are considered to be of dubious social value, is the subject of recent policy debates over the benefits and costs of the procedure (see for example, Federal Register 2006, 2007).

Despite the prominence of continuations in firms' IP strategies and patent policy debates, the arguments over the motives for their use by applicants have been subject to little empirical analysis.⁶⁶ This study links the characteristics of patents and attributes of their publicly listed U.S. owners to these applicants' use of the three major types of continuations (see below for discussion of these three types) in order to test the validity of competing explanations for continuations usage in the patenting strategies of firms. We also examine the effects of the 1995 change in patent term on the incidence of continuations and the characteristics of the corporate users of the procedure.

⁶² "Submarine" patents refer to patents that issue after long periods of secrecy in the USPTO review process and contain claims (often modified during review) that enable their assignee to threaten legal action against users of widely employed technologies for infringement.

⁶³ We do not test the use of continuations to increase uncertainty for rivals' R&D investment decisions or to acquire "submarine" patents, for two reasons: First, the 1995 change in patent term meant that any use of continuations to prolong the examination of a secret patent application results in a shorter patent term. The 1999 changes in U.S. patent law that mandate publication of a large share of patent applications after 18 months further curtailed the efficacy of continuations strategies in raising uncertainty for rivals. Second, testimony by former USPTO commissioner Bruce Lehman states that only 627 patents issued during 1971-1993 fit the definition of submarine patents, and 41% of these were held by the government for security reasons. "Submarine" patents thus appear to constitute too small a share of our sample to be identifiable with conventional statistical techniques (Blount 1999).

⁶⁴ Continuation applications have been available to patentees in the United States since *Godfrey v. Eames*, 68 U.S. 317 (1863). According to the U.S. Patent Office, the procedure is intended to "lead to a well-designed set of claims that give the public notice of precisely what the applicant regards as his or her invention" (Federal Register 2006 p 48).

⁶⁵ During 2005, about 30% of the U.S. Patent Office's patent examining resources were applied to examining continued examination filings that involved revisions of previous applications, in contrast to examining new applications (Federal Register 2006, p 50).

⁶⁶ The USPTO proposed limiting the number of continuations as a matter of right to two per application starting in November 2007 – see Federal Register (August 21, 2007) for further details. These rules were rejected by the United States District Court for the Eastern District of Virginia in 2008 as substantive rather than procedural, and therefore exceeding the rulemaking authority of the USPTO (in *Tafas v. Dudas et al.* and *Smithkline Beecham Corp. et al. v. Dudas et al.*, April 01, 2008).

Our primary finding is that firms use different types of continuations as part of different patenting strategies. One class of continuations, the “Continuation in Part” (CIP) appears to be filed disproportionately by R&D-intensive firms that patent heavily and is more common in chemical and biological technologies. Firms also employ CIPs to cover technologically valuable inventions, and the use of CIPs appears to be consistent with a strategy of protecting “pioneering inventions.” Two other types of continuations, the “Continuation Application” and the “Division” (the following sections discuss the different types of continuations in greater detail), are associated with less valuable patents and used more intensively by capital-intensive firms that patent intensively. This pattern is particularly strong in electronics and computers patents after the 1995 change in patent term, and we suggest that CAPs and Divisions are an important part of firms’ defensive patenting strategies in these and similar industries. In addition to providing the first empirical analysis of the strategic use of continuations by corporate assignees and differences in the three types of continuing applications, the findings of our study inform policy debates over continuations reform.

3.2 Continuations: definitions and use

3.2.1 The patent prosecution process and continuations

Applicants’ decisions on filing continuing applications are best understood within the context of the USPTO patent prosecution process. An inventor starts the prosecution process by filing an application containing a written description of her invention. This description typically includes a number of “claims” that define the invention covered by the application. The examiner compares the claims against the “prior art” embodied in issued patents and other technical publications to determine whether the application meets the standards of patentability. The examination process may result in the application being accepted or rejected in its entirety or (more likely) the rejection of one or more claims by the examiner.

The applicant can respond to a rejection of claims by disclosing additional information showing that her claims are valid, or by modifying them to accommodate prior art and/or the examiner’s suggestions. The examiner reviews this response and may allow the patent claim, suggest modifications, or issue a “final rejection” of the application.⁶⁷ This entire process can go through several rounds and has been characterized as a “give-and-take-affair” between the applicant and the examiner (see Merges 1997 or Popp *et al.* 2004 for an extended description of the patent examination process). At any stage during the prosecution process (*i.e.* when a patent is “pending”) an inventor can file a continuation application with or without substantial modifications to the claims in the original application. The continuation application is treated like a new application, but the filing date of the original application, called the “priority date,” applies to the continued application.

⁶⁷ An applicant faced with “final rejection” can pursue several options, including a Request for Continued Examination (RCE). This RCE is treated like a new application, giving the applicant another chance for her claims to be reviewed while preserving the “priority date” of the original application (Lemley & Moore 2004).

3.2.2 Types of continuing applications

Patent policy debates and existing scholarship on continuing applications (see for instance Lemley & Moore 2004 or Graham & Mowery 2004) seldom distinguish among the three major types of continuing applications: the “Continuation Application” (abbreviated hereafter as the CAP), the “Continuation-In-Part (CIP),” and the “Division.” The CAP discloses the identical invention claimed in the prior “parent” non-provisional application before that application was patented or abandoned. The disclosure presented in the CAP *must be the same* as that of the original application; the continuation can be filed with claims that have been disallowed after initial examination of the original application, but should not include anything that would constitute new matter if inserted in the original application.⁶⁸ The CAP delays a final decision by the USPTO regarding the patentability of some or all of the subject matter claimed in the original application.

The CIP includes a substantial portion or all of the parent application and *adds matter not disclosed in that application*, although the benefit of early priority is awarded only for the claims carried forward from the original application. A Division or divisional application occurs when an original application contains more than one independent invention. In such a case, the USPTO allows the applicant to “elect” one of the disclosed inventions for examination (in response to what is called the “restriction requirement” – see 35 U.S.C. 121). The other inventions disclosed in the original or “parent” application can be withdrawn and pursued in new applications called Divisions. An application can be filed as a division and thereby benefit from the early filing date of the parent application only if it discloses and claims subject matter disclosed in the parent application.

All three types of continuations introduce a delay in the prosecution and final issue decision for a U.S. patent and permit the applicant to adopt the date of the application that is still pending within the Patent Office.⁶⁹ A patent can also issue from more than one of the three continuation types, and about 16% of all continued patents belong to this category, one that we refer to as “Combination” continuations. Since we cannot disentangle the strategies for filing the three types of continuing applications for patents issuing from more than one type of continuation, we do not discuss the “Combination” category in detail.

3.2.3 Continuations, patent characteristics, and applicant characteristics

Our hypotheses regarding the strategic uses of continuations are derived from interviews with corporate IP managers in various industries and an examination of the nearly 300 responses from inventors, law firms, corporations, and industry organizations that were filed in response to the USPTO’s 2006 request for comments from continuations users regarding the changes to the procedure that were to take effect (until overturned by the federal courts)

⁶⁸ The fee required to request a continuing application is no higher than that for filing a first application: \$710 in 2001, and \$355 for small entities. 37 C.F.R.17 (e).

⁶⁹ All continuing applications must meet certain conditions. Under 35 USC § 120, a patent application is entitled to adopt the filing date of a “parent” application when (1) both applications disclose the same invention; (2) both applications are filed by the same inventor; (3) both applications are simultaneously co-pending; (4) the earlier application meets the disclosure requirements of 35 USC § 112; and (5) the later application contains a specific reference to the earlier application. *Sampson v. Ampex Corp.* (1971, DC NY), 333 F. Supp. 59, *aff’d.* (2nd Cir. NY) 463 F2d 1042.

in November 2007 (USPTO 2008). Our empirical analysis focuses on the validity of two characterizations of continuations use that were highlighted in these comments and interviews. The first argues that continuations are used by “pioneering” corporate inventors in relatively new fields of inventive activity, where claims may require modification after the filing of an application. A very different characterization claims that continuations are used mainly by large firms as part of “defensive patenting” strategies that seek to avoid costly injunctions that can shut down capital-intensive production facilities.

The “pioneering inventor” characterization of continuations suggests that they are used by firms to acquire strong patent rights in fields of inventive activity in which the “science” underpinning the patent application is new and uncertain. According to several scholars, strong patent rights are particularly important for small science-based or R&D intensive firms that lack downstream assets such as manufacturing or marketing capabilities to commercialize their inventions (see Hall and Ziedonis, 2001, among other analyses). These R&D-intensive firms use patents to license their inventions or to attract finance from external sources. They include “boutique” chemical firms, biomedical startups, suppliers of intermediate technological inputs in aerospace and instruments, and “fables” design firms in semiconductors (Arora *et al.*2001). Comments by the Chief Operating Officer of the Biotechnology Industry Organization (an industry organization with a membership of more than 1,100 biotechnology companies, academic institutions, and related organizations) on the proposed USPTO revisions in continuations summarize this characterization of continuations use by pioneering inventors:

“Competitive pressure drives smaller biotechnology companies to file patent applications on inventions early in the development stage so that they may obtain that first patent to generate investor interest...Consequently, biotechnology companies file patent applications years before a product or technology has been fully developed or commercialized. During this time, they may agree to initial narrow patents and continue to perform ‘proof of concept’ experiments to further support their initial discovery. With the initial patent in hand, patent owners can point to other pending applications (continuations) that are broader and more comprehensive to secure further investor interest. While biotechnology patent applicants expect and often are entitled to broader claim coverage without additional information, they may not expend the resources to obtain a broader claim unless the area becomes an area of commercial focus” (Scott Whittaker, p 4, May 2, 2006).

These comments suggest that continuations are used by R&D-intensive firms that patent intensively to protect their technologically valuable intellectual property.

Other patent attorneys and scholars argue that applicants use continuations to “wear down” USPTO examiners and obtain patents with dubious claims (see for instance, Quillen & Webster 2001 and Lemley & Moore 2004). Robert Barr, former chief patent counsel for Cisco Inc., stated that a common strategy for firms in the communications industry is to use continuing applications to “leave the junk behind,” *i.e.* to obtain patents with “strong” claims that are allowed by the patent examiner first and to subsequently pursue weaker claims in

continuing applications (personal communication, 25 September 2007). In a similar vein, Merges *et al* (2003) observe that a “typical prosecution strategy is to take the bird in the hand and fight over the contested claims separately” by filing continuing applications (p 116).

A patenting strategy that is consistent with the use of continuations to acquire a large number of less significant patents has been analyzed by Hall & Ziedonis (2001) in the semiconductor industry. For capital-intensive manufacturing firms, whose multibillion-dollar production facilities are at risk of shutdowns from patent-infringement injunctions, large patent portfolios can be useful in cross-licensing negotiations that reduce the risk of patent litigation. For example, IP managers at Micron and Intel “...see another purpose [in intensive patenting]: to preserve their own freedom of action. If they are first to patent a new way to improve their chips, competitors will have a hard time stopping them from using it.” (Wall St. Journal, 13 March 2007). The managers of such capital-intensive firms acknowledge that patents are of little importance in appropriating the returns to innovation and the technological value of the individual components of the large patent portfolios of these firms accordingly may be low.

These seemingly contradictory characterizations concerning continuations’ use yield testable implications. If continuations are used by “pioneering inventors” to insert claims in response to advances in the science underlying their patents, continuations should be associated with technologically more significant inventions and should be assigned to R&D-intensive firms operating in fields in which patents are important in capturing the returns to innovation. Further, because CIPs are continuations that allow applicants to insert previously undisclosed matter related to the invention covered by the “parent” application, we expect CIPs to be used extensively by R&D-intensive firms to protect technologically significant inventions. Firms that rely less heavily on patents to protect their intellectual property may forgo the use of continuations because of the additional costs and delay induced in the prosecution of patents by the procedure. Hence, we propose the following testable implications relating the CIP to firm and invention characteristics:

H1a: Continuations-In-Part (CIP) applications are more likely to be filed by R&D-intensive firms that patent intensively.

H1b: Continuations-In-Part (CIP) applications are more likely to be filed by firms to protect inventions of high technological value.

The “defensive patenting” use of continuations, by contrast, implies that individual patents issuing from continuations represent a less significant innovative step, *ceteris paribus*, and that these patents will be assigned to capital-intensive firms that patent intensively in technologies for which patents play a less significant role in capturing the returns to innovation. The rules governing their use make CAPs useful for pursuing claims that were rejected during initial rounds of examination, provided that no new matter is introduced. Divisions can also be used by patentees to file an application with a large number of claims and obtain an early patent covering a subset of these claims while continuing to argue for additional patents that cover the “leftover” claims. Hence, we expect that defensive patentees are more likely to utilize CAPs and Divisions, and propose the following hypotheses regarding the relationship between CAPs and Divisions, and the characteristics of firms and their inventions.

H2a: Continuation applications (CAP) and Divisions are more likely to be filed by capital-intensive firms that patent intensively.

H2b: Continuation applications (CAP) and Divisions are more likely to be filed by firms to expand a portfolio of technologically less valuable patents.

3.3 Methodology and data

Our empirical analysis examines the characteristics of corporate assignees using different types of continuations and the characteristics of patents that emerge from these continuations. This analysis uses data from the USPTO on U.S. utility patents granted to U.S.-owned businesses between 1981 and 2004. We gathered the continuations history of each patent from the “Related Patent Data” on the wrapper of the patent document, which reports the type of continuation applied for and its application date. We calculated the “priority date” as the date on which the first in a series of continuation applications was filed. For patents that were never subject to the continuations procedure (referred to below as “ordinary” patents), the priority date is the first and only application date. We retain in our analysis only those patents with priority dates between 1981 and 2000 that were issued during 1981 – 2004.⁷⁰ We separate patents that issued from only one type of continuation (the CAP, CIP, or Division) from those that resulted from multiple continuation types (“Combination” continuations).

Linking patent information to firm-level attributes is complicated by the fact that firms patent under various names and assignee names may not accurately reflect the corporate ownership of patents. We used the NBER PTO-Compustat correspondence file to assemble a set of unique patenting entities by identifying firm acquisitions, mergers, name changes, and majority-owned subsidiaries between 1981 and 2000.⁷¹ This yielded matches for 2,263 patent assignees to 1,273 unique Compustat firms that collectively owned 363,308 patents, representing 38% of all patents assigned to U.S.-owned businesses between 1981 and 2004. Since firms enter and exit the data during the period of observation, with some instances of multiple entry and exit, our sample is an unbalanced panel.

The continuations propensity of publicly traded large firms represented in Compustat that we include in our dataset differs from that of privately held firms. Our “in-sample” patents assigned to public companies were more likely to have issued from CAPs and Divisions, but less likely to have used CIPs than the “out of sample” patents assigned to U.S.-owned entities

⁷⁰ Patents that are not subject to continuations are granted an average of 2.2 years after the date of first application (standard deviation of 1.1), but applications subject to the procedure pend for 4.4 years (s.d. of 2.3) on average. The longer pendency for continued patents introduces a bias that overrepresents applications that are not continued in the population of granted patents during the later years. Restricting the last year of priority dates to 2000 in all patents granted through the year 2004 minimizes this bias.

⁷¹ The NBER file reflects the ownership status of firms as of 1989. The file was constructed by assembling U.S. patents assigned to unique firms by identifying name changes, subsidiaries, and merger and acquisition information from a variety of sources (Lexis/Nexis business directories, 10-K filings, and the Directory of Corporate Affiliations).

not listed in Compustat. Accordingly, we make no claims that the results of our analysis are representative of the patenting and continuations behavior of all U.S. firms.

3.3.1 Continuations use in different technology classes

The economic value of patents varies considerably among technologies (Levin, Nelson, Klevorick, & Winter 1987; Cohen, Nelson & Walsh 2000). Patents in “complex” product industries (*e.g.*, electrical machinery, electronics, and instruments) in which a single product may contain intellectual property covered by hundreds of patents are typically described by IP managers as less valuable than patents in “discrete” product industries such as drugs, pharmaceuticals, and chemicals (Hall 2004). Despite their more modest importance in complex product industries, firms in these sectors may accumulate large patent portfolios as part of defensive strategies (Hall & Ziedonis 2001).

We used the NBER classification developed by Hall, Jaffe and Trajtenberg (2001) to aggregate the more than 500 USPTO technology classes into 36 two-digit technological subcategories for use in our regression analyses and further aggregated these 36 subcategories into 6 categories for ease of descriptive discussion: Chemical; Drugs and Medical; Electrical and Electronics; Computers and Communications; Mechanical; and a miscellaneous “Other.” Consistent with the above characterizations, we find that patents in “complex” product industries (Electrical & Electronic products, Computers & Communication, Mechanical) are less likely to emerge from continuations of any type (See Figure 3.1). In the Computers & Communications sector, however, CAPs, which are particularly well-suited to the “wearing down” of an examiner, account for 50% of all continuations.

Continuations are more common for patents in the “Drugs and Medicine” and “Chemicals” technology classes. Continuations overall account for 44% of the patents issued in “Drugs and Medicine” for priority years 1981-2000, and 34% of those issued in “Chemicals” during the same period. CIPs account for the majority of continuations (30%) in these two technology classes. The intensive use of CIPs in the two “discrete” product industries may reflect the use of continuations for modifying claims during the examination of applications for patents of strategic importance.⁷²

3.3.2 Continuations and technological “value”

Our analysis seeks to determine whether corporate assignees use continuations to protect pioneering inventions of high technological importance or to acquire a large number of patents of more marginal technological importance.⁷³ For this purpose, we use forward citations as indicators of the technological importance of patents, based on the argument that a higher number of citations to a patent in subsequent patents indicate that the

⁷² More detailed technology-specific analyses, as well as various empirical estimations that we mention here, but do not report owing to length considerations can be accessed from our analyses and supplementary appendix available at: <http://www.nber.org/papers/w13153>

⁷³ We also examined 4-year renewal probabilities to investigate the relationship between the private value of patents and continuations behavior. We found that CAPs are most likely and Divisions least likely to be renewed. These differences in renewal probabilities, which suggest an ambiguous link between technological and private value, nonetheless were not statistically significant.

invention in the cited patent influenced the development of a greater number of subsequent inventions (Jaffe, Trajtenberg & Henderson 1993).

Since forward citations arrive after a patent has been granted, they can arrive at any point of time in the patent's life, and older patents are likely to accumulate more citations. This truncation problem means that patents granted in more recent years will appear to be less technologically important, on average. Restricting forward citations to a 4-year window (including the year in which the patent was issued) eliminates this problem and enables us to examine forward citations for patents granted through 2004, the last issue year for patents in our data.

Table 3.1 reports descriptive statistics for the number of forward citations received by patents within 4 years of their issue that result from different types of continuations in different technology classes. Patents issuing from CIPs consistently receive more citations on average than patents associated with any other type of continuation, and patents issuing from divisions receive the fewest. CAPs produce patents that are significantly less technologically important than ordinary patents in electrical and electronic technologies and more important than ordinary patents in computers and communications. In all other technology classes, the average number of forward citations associated with CAP-linked patents does not differ significantly from the average forward citations associated with ordinary patents. Table 3.1 highlights significant differences among technologies in the number of citations received by patents, as well as similarities in the average number of forward citations for patents issuing from different continuation types across technology classes.

3.4 The empirical specification

We analyze the choice of continuation ($j = \{0, 1, 2, 3, 4\}$, representing “no continuation”, CAP, CIP, Divisional or a “combination”⁷⁴) as determined by a mix of invention- and firm-level attributes (\mathbf{x} ' represents the vector of these factors). The conditional probability 'y' of each continuation type can be estimated by specifying a multinomial logit (MNL) choice model.⁷⁵ Since the probabilities sum to unity, $P(y = 0 \mid \mathbf{x})$ is determined once we know the probabilities for $j = 1, \dots, 4$. The conditional response probability for continuation type 'j' is given by (Wooldridge 2004):

⁷⁴ As previously noted, we include “Combinations” (patents issuing from multiple continuation types) in our estimations, but do not attempt to interpret these results from our analysis, since such “combinations” do not admit of any straightforward interpretation of motives or effects.

⁷⁵ The MNL model assumes the independence of irrelevant alternatives (IIA). In our context, the assumption implies that adding or deleting a continuation type alternative does not affect the odds among the remaining alternatives. This seems particularly plausible, given that the continuation types (CAP, CIP and Division) are procedurally distinct, and can be weighted independently of each other by the applicant. Tests such as the Hausman-McFadden and the Small-Hsiao while imperfect (see Cheng & Long 2005), also indicated that the IIA assumption was valid for our sample.

$$P(y = j | \mathbf{x}) = \frac{\exp(\mathbf{x}\boldsymbol{\beta}_j)}{\left[1 + \sum_{h=1}^4 \exp(\mathbf{x}\boldsymbol{\beta}_h)\right]}, \quad j = 1, \dots, 4 \quad (1)$$

The effect of each explanatory variable ‘ x ’ on $P(y = j)$, that is, the conditional probability of the type of continuation ‘ j ’, is given by the corresponding β_j .

3.4.1 Independent variables: Patent and firm characteristics

Our explanatory variables highlight selected characteristics of corporate assignees and patents, including corporate R&D intensity (R&D investment normalized by employment) and patent intensity (number of issued patents in year t , normalized by same-year R&D investment). In addition, we interact corporate patent intensity with R&D intensity ($RDINT*PATINT$) to identify the R&D-intensive firms that patent intensively. Another interaction term, $PATINT*CAPINT$, identifies capital-intensive firms that patent heavily. The patent characteristic that is of particular interest for our empirical analysis is the technological importance of a patent, proxied by the number of forward citations obtained by the patent within the first four years following its issue.

We include two other variables to capture the effects of firms’ patent portfolios on their continuations strategies. The “centrality” of a patent within a firm’s portfolio, $TECHSHARE$, is defined as the share of the patent’s technology class in the “flow” of patents issuing to a firm each year. The value of $TECHSHARE$ is bounded above at one when a firm’s patents for a given year are all assigned to the same technology class within our 36-category taxonomy. The patenting experience of firms in individual technology areas, $TECHTIME$, is computed as the difference in years between the year of a given patent’s application year and the year in our dataset in which the firm was first assigned a patent in that class.

We control for other factors that may influence a firms’ continuations choice probabilities and its patent strategy. The most obvious of these factors are the technological field in which a firm patents and the industry in which it operates. We include 36 patent technology-class dummies (based on NBER classification) and 13 industry categories (based on 2-digit SIC class) to control for unobserved inter-industry and inter-technology heterogeneity. Patent priority-year fixed effects control for factors such as changes in patent law, trends in citation rates that are common across all firms, and other characteristics that influence firms’ R&D investment decisions and patenting strategies. We include the log of employment as a control for firm size, since complex patenting strategies, *e.g.* the cost of maintaining an in-house staff of patent attorneys, can create higher fixed costs, and therefore may be correlated with patent and R&D intensity. The age of firms is included to capture effects due to experience and learning that are not captured by firm size.

Table 3.2 reports descriptive statistics for the chief variables in our analysis. The median Compustat firm in our sample has about 4,000 employees, spends \$14.5 million annually on R&D, has capital assets totaling \$ 250 million, and successfully applies for 6 patents a year. In summary, we are testing the influence of the following explanatory variables on the continuations choice probability of corporate patentees:

(i) *lnPATINT*: the patenting intensity of firms, calculated as annual log number of patents/ M\$ of annual R&D (the suffix '*ln*' indicates the natural log of variables)

(ii) *lnCAPINT*: the capital intensity of firms (log book value of plant, property and equipment in M\$/1000 employees)

(iii) *lnRDINT*: the R&D intensity of firms (log annual R&D expenditure in M\$/1000 employees)

(iv) *lnPATINT * lnCAPINT* (multiplicative interaction of i & ii).

(v) *lnPATINT * lnRDINT* (multiplicative interaction of i & iii).

(vi) *FCITES*: the technological importance of the invention, measured by forward citations received within 4 years of the patent's issuance.

Our control variables include:

(i) *TECHSHARE*: the technological relevance of a firm's application to its current focus captured by the share of its technology class in the firm's patent portfolio.

(ii) *TECHTIME*: the patenting experience of a firm in a particular technological area, calculated as the difference between a patent's application year and the year of the firm's first application for an issued patent in that class.

(iii) the size of firms measured by log of employment.

(iv) log of firm age.

(v) industry-specific dummies, technology-specific dummies, and priority-year dummies.

3.5 Results

Our specifications are estimated with maximum likelihood methods and the results are reported in Table 3. The absolute values of the MNL estimates are not particularly meaningful, and we focus on the qualitative interpretation (relative size, signs, and statistical significance) of the coefficients for the independent variables in Table 3.3. All coefficients convey *ceteris paribus* effects and should be interpreted as reflecting the influence of the relevant independent variable relative to patents with no continuations in their history ($j=0$).⁷⁶

The interaction terms significantly influence the choice among continuation types in ways that are broadly consistent with our hypotheses. The influence of *lnPATINT*lnRDINT*

⁷⁶ Since this is a nonlinear model, the effect of any independent variable depends on the values at which the other independent variables are held constant. Hence, we also calculated changes in the choice probabilities when a particular 'x' of interest changed with respect to meaningful values of the variables, with the values of all other independent variables at their sample averages. See Note (d) under Table 3.

(which we associate with pioneering inventors) is positive and statistically significant in explaining the use of CIPs, meaning that an increase in R&D intensity increases the probability of CIP filings for firms that patent intensively. In contrast, the $\ln PATINT * \ln CAPINT$ variable (which we associate with defensive patenting) positively and significantly affects the probability that CAPs and Divisions are used, but is significantly less likely to be associated with CIPs.⁷⁷ The technological importance of a patent affects continuation choice, as revealed in the negative and statistically significant coefficients for *FCITES* in Table 3.3; CIPs are associated with patents that receive larger numbers of forward citations, and CAPs and Divisions are associated with patents that are on average cited less frequently than “ordinary” patents. Firm size (employment) is inversely related to CIP filings, but positively correlated with the probability of CAPs and Divisions. These results are broadly consistent with the view that CIPs are more likely to be used by smaller “pioneering inventors,” in contrast to CAPs and Divisions, which are more likely to be used by large corporate patentees in obtaining patents of lower importance.

The negative sign of the statistically significant *TECHTIME* coefficient means that for all types of continuations, the longer the time period since a firm’s first patent in the same technological area, the less likely a current patent is to be continued. In other words, the more recently a firm has become active in patenting within a given technology class, the greater the chances that it will use one of the four types of continuations. Hence, all types of continuations are used more frequently when firms are patenting in areas in which they have not previously been active, a finding that may reflect a tendency for patent applicants to use all continuations types more intensively in fields in which corporate patentees have less experience and therefore may be more likely to seek revisions in their applications.⁷⁸ Patents in areas central to a firm’s annual flow of patents (*TECHSHARE*) are significantly more strongly associated with the use of continuations procedures, a finding that tends to undercut the characterization of continuations as associated with entry into a new field of patenting.

Finally, we estimated continuation choice probabilities for patents in each of the five major technology classes (estimates of these regressions are not reported and available from the author). The coefficients for our explanatory variables were broadly similar to those reported in Table 3.3 for the “all technologies” fixed-effects model, with the following noteworthy differences. The variable interacting capital intensity and patent intensity had a greater positive influence on CAP/Division probabilities in electrical & electronics and

⁷⁷ We also estimated our model with 1-year, 2-year and 3-year lagged values of the dependent variables in response to an anonymous referee’s concern that the choice of continuations may be contemporaneously determining firm attributes such as patent intensity. The coefficient estimates on the lagged variables do not differ significantly from those reported in Table 3.

⁷⁸ We appreciate comments from an anonymous referee in highlighting this point. We also tested the influence of the age of the technological areas in which a firm is patenting on the continuations behavior of firms. We measured the age of the technological area by the difference between the application year of a patent and the application year for the first patent issued in the patent’s class. The results suggested that the technological age of an invention has a statistically significant and negative impact of firms’ propensity to file continuations, i.e., firms are less likely to use continuations for patents in older fields. However, the inclusion of technological age did not affect the coefficient estimates for the other variables in the specification, nor did its influence vary among the three types of continuations. The size of this effect was also marginally small and we do not report these estimates here.

computers & communication, but was negligible for chemicals and negative for drugs & medicine patents. Evidence for the “defensive patenting” characterization of CAP and Division filings is particularly strong for computers and electronics, while the chemicals field strongly supports the “pioneering inventor” use of CIPs.

3.6 The effects of the 1995 change in patent term on continuations behavior

As we noted earlier, legislation passed in December 1994 changed the term for patents issuing after June 1995 to twenty years from the application date from the former term of 17 years following the issue date. The change in patent term was motivated in part by congressional concerns over the “abuse” of continuations in submarine patenting strategies. This section examines the effects of the law on the use of continuations, posing the following three questions: (a) did the law reduce the use by corporate assignees of continuations?; (b) given that one motive for the 1995 change was curbing the “abuse” of continuations, did the “technological importance” of patents resulting from continuations change after 1995?; and (c) how if at all did the 1995 change in patent term affect the characteristics of the corporate assignees using continuations?

The time trends depicted in Figure 3.2 show that use of all continuation types by U.S. businesses increased as a share of issued patents through 1994 and decreased thereafter. The post-1994 decline was especially noteworthy for CAPs and within this continuations class was most pronounced for the Computers & Communications industry -- nearly 25% of all patents first applied for in 1993 in this technology class resulted from CAPs, but by 1996, this share had declined to 9%.⁷⁹ The share of CIPs and Divisions in all of the five major technology categories declined less sharply after 1995.⁸⁰

We use our Compustat sample and the continuations choice model described in Section 3.4 to investigate changes in the attributes of patents and corporate continuations users after

⁷⁹ The truncation problem affects calculations regarding the magnitude of post-1995 decline in continuations use. An analysis of the distribution of pendency lags suggests that patents with a 1996 priority year are underrepresented by 6%, 1997 priority-year patents by 10% and so on. The overall data, however, show that patents from continuation applications dropped by 28% in 1996 and by 34% in 1997 as compared to 1994 levels. Hence, the post-1995 drop in continuations cannot be solely attributed to truncation effects.

⁸⁰ Other changes in patent application procedures after 1995 make it difficult to conclude that the 1995 change in patent term is the sole cause of the sharp decline in CAPs. Conversations with patent attorneys revealed that the patent term change in 1995 was accompanied by the introduction of a new procedure called the “Continued Prosecution Application” (this *CPA* was superseded for utility patents by the Request for Continued Examination, RCE, in 2003) that allowed applicants to keep the prosecution of an application alive even after “final rejection” by the examiner. Before 1995, an applicant facing a “final rejection” from the Patent Office was required to abandon the application before filing what was called a “File Wrapper Continuation” (FWC) for continued prosecution. The USPTO treated the FWC identically to the CAP and as a consequence, our pre-1995 CAP patents may include those issuing from FWCs, a group that after 1995 is excluded by virtue of being included in the CPAs. Without controlling for the FWC/CPA/RCE conflation, it is difficult to ascribe the decline in CAPs entirely to the 1995 change in patent term.

June 1995, dividing the sample into a pre-June 1995 panel and a panel that includes patents with priority dates of June 1995 and later. Table 3.4 compares the estimates obtained by estimating our choice model separately for the two panels.

The coefficients on *FCITE* show that patents issuing from all types of continuations after June 1995 are cited less frequently.⁸¹ The 1995 change in patent term may have reduced the willingness of applicants with valuable inventions to accept a curtailed patent term in exchange for the benefits associated with a continuation.⁸² R&D-intensive firms that patent heavily are less likely to use all three types of continuations after 1995,⁸³ but the positive influence of the interaction of capital- and patent-intensity on the likelihood of CAP and Division filings increases for the June 1995- December 2000 period. These results suggest that post-1995 CAPs and Divisions are more likely than pre-1995 CAPs and Divisions to be used for inventions of lower technological importance, and they are used more intensively after June 1995 by firms with characteristics associated with users of defensive patenting strategies. The results in Table 3.4 suggest that the importance of patents issuing from CIPs also declines slightly after the change in patent term, while the coefficient for the variable that we view as most clearly associated with the “pioneering inventor,” *RDINT*PATINT*, loses its statistical significance. The corporate characteristics that we identify with “defensive patentees,” however, retain a negative and significant coefficient in predicting the choice of CIPs for the post-June 1995 period.⁸⁴

3.7 Concluding remarks

The continuations procedure allows patent applicants to alter the scope and timing of issued patents in response to technological developments and potentially, the patenting activity of competitors. Despite their widespread use by U.S. corporate assignees (29% of all issued patents during 1981-2004 involved continuations), the procedure has received little attention from scholars of patent strategy. The limited prior research on the topic, as well as policy debates regarding the uses and abuses of continuations, also has not probed variations

⁸¹ Patents applied for between 1981 and 2000 appear in this analysis only if they were granted by 2004. Consistent with our earlier procedure, we employed a 4-year “window” for forward citations for all patents in the dataset in order to minimize truncation bias. The “4-year window” includes forward citations from the same year as the issue of a patent and three subsequent years. The last year for citing patents for patents issued in 2004 is 2006 and we ensured that this truncation of citations for patents granted in the last two years of our analysis does not affect our observations.

⁸² This decline in the importance of post-1995 CAPs is not affected by the FWC/CPA/RCE problem described earlier. Applicants that might have resorted to a CAP in response to a “final rejection” of an application are present in the pre-1995 panel, but are excluded from post-1995 observations.

⁸³ We also examined the effects of firm-attributes on continuations choice for each of the five major patent technology classes and found that “defensive patentees” are more likely, and “pioneering inventors” less likely to choose CAPs in their patents after 1995 in all sectors.

⁸⁴ A high proportion of backward self-cites is another potential correlate of patenting strategies that accumulate “thickets” of patents that overlap and cite one another. We found that patents owned by Compustat firms issuing from post-1995 CAPs contained a significantly higher proportion of backward *self*-citations than any other group of patents, while CAPs prior to 1995 cited their own patents *less* frequently than patents issuing from any other type of continuation. This provides additional evidence on the increased use of CAPs in post-1995 strategies that involve building thickets of patents.

among the three types of continuations. By examining the characteristics of U.S. patents issuing from the three types of continuations between 1981 and 2004, and the characteristics of these patents' corporate assignees, we have tried to provide some evidence on the role of continuations in U.S. firms' patenting behavior.

Continued patents pend for twice as long as patents without continuations in their review history. The "Continuation in Part" is used by inventors to insert additional material to a pending patent application and produces patents with the highest number of claims, forward citations, and renewal probability. Patents in Drugs, Medicine, and Chemicals – industries in which patents are widely rated as important for capturing the returns from innovation – use CIPs more intensively. CIPs are also more likely to be filed by smaller firms in our sample and are associated with patents of higher technological importance. These results imply that CIPs are used by firms to secure an early priority date while preserving the option of revising claims during review of their applications in technologies where patents are important to appropriate the returns to R&D. In at least some respects, these characteristics of CIP patents and assignees are broadly consistent with the claims by some interest groups that the continuation supports the inventive efforts of "pioneering inventors."

The "Continuation Application" (CAP) and the Division produce patents covering inventions of more modest technological importance than those issuing from the CIP. The CAP, which extends the pendency period of an application that does not include new claims, is the most common type of continuation among Computers, Communication, and Semiconductor patents that use continuations (accounting for nearly half of all continuations filed in these technologies during 1981-2000). These technologies are characterized by rapid change, short technology cycle times, and a more modest role for patents in capturing the returns to innovation. CAP applicants, particularly those filing applications after 1995, also disproportionately cite their own previous patents as prior art. Divisions, like CAPs, can be used in patent applications that contain a large number of claims to obtain patents containing a subset of the claims at later dates. These observations, combined with our findings that CAPs and Divisions are frequent among the low-value patents of firms that patent intensively and have large sunk costs, are broadly consistent with a "defensive patenting" interpretation of the two types of continuations in patent strategy.

Finally, our analysis of the 1995 change in patent term suggests that the Act decreased continuations filings and forced IP managers to trade off patent duration for the extended prosecution time associated with continuing applications. The result of this tradeoff is manifest in the lower average technological importance of patents issuing from all the three types of continuations for patents filed after 1995.

What implications do our analyses have for the patent and continuation reforms recently discussed by the Patent Office and the U.S. Congress? The USPTO's 2007 reform proposals included a requirement that the third and subsequent continuations of an application should "include a showing as to why the amendment, argument, or evidence presented could not have been previously submitted" (Federal Register 2007). Although such petitions impose significant additional burdens on the patent office, they could aid patent examiners in evaluating continuation applications more effectively. Our results do not support a definite characterization of the CIP as prone to abuse before or after 1995, but they do suggest that skepticism concerning the benefits of the CAP is warranted. Hence,

reform of the patent prosecution process can benefit from a closer consideration of the type of continuation filed by applicants and might contemplate differential treatment of the different continuation types.

Chapter 3 Figures and Tables

FIGURE 3.1: CONTINUATIONS BY PATENT TECHNOLOGY CLASS
(ISSUE YEAR: 1981-2004, PRIORITY YEAR: 1981-2000)

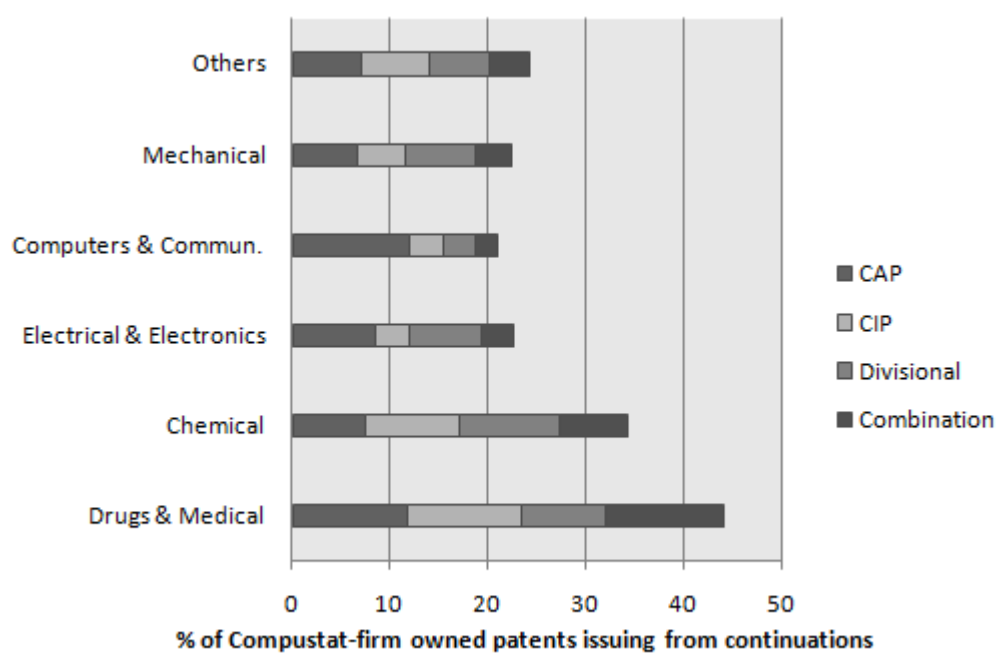


FIGURE 3.2: TRENDS IN CONTINUATION TYPES
(ISSUE YEAR: 1981-2004, PRIORITY YEAR: 1981-2000)

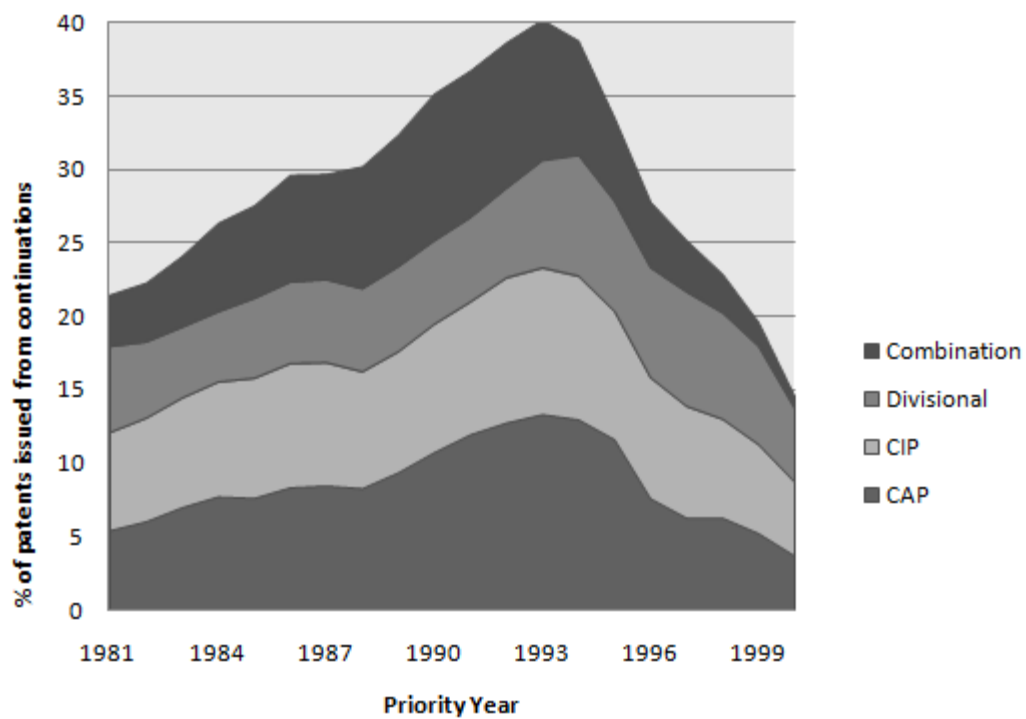


TABLE 3.1: TECHNOLOGICAL “VALUE” OF CONTINUED PATENTS BY TECHNOLOGY CLASS

4-Year Forward Cites	Chemicals	Drugs & Medical	Electrical & Electronic	Computers & Commun.	Mechanical	Others
"Ordinary" patent	1.69 [2.7]	2.3 [3.74]	2.76 [3.93]	3.66 [4.92]	1.84 [2.8]	1.72 [2.5]
CAP	1.68 [2.62]	2.29 [3.85]	2.51 [3.38]*	3.95 [5.15]*	1.84 [2.88]	1.73 [2.35]
CIP	2.1 [3.07]*	2.59 [4.01]*	3.34 [4.47]*	4.75 [6.05]*	2.37 [3.67]*	2.18 [2.88]*
DIV	1.01 [1.92]*	1.59 [3.69]*	2.56 [3.86]*	3.03 [4.17]*	1.49 [2.62]*	1.24 [1.97]*

Standard deviations in brackets;
 * indicates a statistically significant difference ($p < 0.001$) from means of Ordinary patents in technology class

TABLE 3.1 NOTES: (a) This table is based on the 363,308 patents owned by 1273 unique Compustat firms with priority years 1981-2000, and issued between 1981-2004. (b) Citations from U.S. patents within a 4-year window from the issue date of patents (including the issue year) proxy for the technological value of the patented invention.

TABLE 3.2: DESCRIPTIVE STATISTICS FOR COMPUSTAT FIRMS (BASED ON 9096 COMPUSTAT FIRM-YEAR OBSERVATIONS)

Variables	Median	Mean	SD	Min	Max
Employment (in 1000s)	4.21	17.86	45.33	0.01	876.80
Capital Assets (M\$ of property, plant, & equipment)	249.15	1986.56	6392.52	0.05	171895.80
Capital Int. (M\$ of property, plant, & eqp/1000 emp)	59.75	88.13	99.95	0.06	1983.62
R&D (M \$)	14.53	119.79	392.68	0.00	5227.00
R&D Intensity (M \$ / 1000 emp)	3.65	9.38	19.67	0.00	426.18
Number of patents	6.00	39.34	135.49	1.00	3873.00
Patent Intensity (Patents/M \$ R&D)	0.48	1.10	2.80	0.00	100.00
Tech Share (Share of patents from primary class)	0.57	0.50	0.35	0.00	1.00
Tech Time (Priority year - first P. year in tech class)	5.90	5.00	5.47	0.00	19.00
Age	19.00	18.68	10.53	1.00	41.00

TABLE 3.3: MULTINOMIAL LOGIT ESTIMATES OF CONTINUATIONS DECISIONS (PRIORITY YEARS 1981-2000, ISSUE YEARS 1981-2004)

Dependent variable: continuation type			
Explanatory variables	<i>CAP</i> ($j=1$)	<i>CIP</i> ($j=2$)	<i>Div</i> ($j=3$)
lnRDINT*lnPATINT	-0.012 [0.007]	0.064 [0.008]**	-0.04 [0.008]**
lnCAPINT*lnPATINT	0.153 [0.010]**	-0.07 [0.011]**	0.216 [0.012]**
FCITES	-0.023 [0.002]**	0.033 [0.002]**	-0.09 [0.003]**
lnPATINT	-0.539 [0.041]**	0.262 [0.046]**	-0.703 [0.050]**
lnRDINT	0.162 [0.011]**	0.07 [0.013]**	0.27 [0.013]**
lnCAPINT	0.145 [0.014]**	-0.006 [0.017]	-0.007 [0.017]
TECHSHARE	0.51 [0.036]**	0.485 [0.042]**	0.206 [0.043]**
TECHTIME	-0.062 [0.003]**	-0.032 [0.004]**	-0.054 [0.003]**
ln employment	0.019 [0.007]**	-0.056 [0.008]**	0.027 [0.008]**
lnAGE	-0.058 [0.011]**	-0.002 [0.012]	0.033 [0.012]**
Constant	-5.028 [0.295]**	-2.918 [0.279]**	-3.929 [0.366]**
Total Observations	356753		
Model chi-square	57923.42		
Standard errors in brackets; * significant at 5%; ** significant at 1%			

TABLE 3.3 NOTES: (a) The table is based on the 363,308 patents owned by 1273 unique Compustat firms with priority years 1981-2000, and issued between 1981-2004. The actual number of observations (356,753 patents) used in maximum likelihood estimations are the ones with complete data on all the included variables (b) Base class: no continuation ($j=0$); Combinations ($j=4$) included, but not reported. (c) Industry-, Patent Technology class & Priority-year effects included, but not reported. (d) The effect of the variable lnRDINT*lnPATINT for change from its minimum value to its maximum value, evaluated at the sample mean values of other explanatory variables is respectively -0.04, 0.10, and -0.15 on the relative probability of CAP, CIP and Division filings; the effect of the lnCAPINT*lnPATINT variable for change from its minimum value to its maximum value, evaluated at the sample mean values of other explanatory variables is respectively 0.25, -0.58, and -0.60 on the relative probability of CAP, CIP and Division filings; similarly, the effect of FCITES is respectively -.08, 0.79, and -0.06 on the relative probability of CAP, CIP and Division filings respectively.

TABLE 3.4: THE 1995-POLICY CHANGE & MLNM ESTIMATES OF CONTINUATION CHOICES (PY1981-1994 & PY1995-2000, ISSUE YEARS 1981-2004)

Explanatory vars.	PANEL-A (PY81-May95)			PANEL-B (PY Jun95-Dec00)		
	<i>CAP</i> (<i>j=1</i>)	<i>CIP</i> (<i>j=2</i>)	<i>Div</i> (<i>j=3</i>)	<i>CAP</i> (<i>j=1</i>)	<i>CIP</i> (<i>j=2</i>)	<i>Div</i> (<i>j=3</i>)
lnRDINT*lnPATINT	0.015 [0.009]	0.052 [0.010]**	-0.006 [0.011]	-0.133 [0.015]**	0.003 [0.016]	-0.106 [0.015]**
lnCAPINT*lnPATINT	-0.1 [0.013]**	-0.118 [0.014]**	0.109 [0.016]**	0.49 [0.023]**	-0.094 [0.026]**	0.352 [0.022]**
FCITES	-0.002 [0.002]	0.047 [0.002]**	-0.074 [0.004]**	-0.085 [0.004]**	0.015 [0.003]**	-0.114 [0.004]**
lnPATINT	0.428 [0.050]**	0.512 [0.058]**	-0.322 [0.066]**	-1.719 [0.119]**	0.461 [0.126]**	-1.182 [0.115]**
lnRDINT	0.194 [0.013]**	0.149 [0.015]**	0.278 [0.017]**	0.174 [0.024]**	-0.146 [0.024]**	0.247 [0.023]**
lnCAPINT	-0.116 [0.017]**	-0.001 [0.021]	-0.213 [0.023]**	0.538 [0.035]**	-0.031 [0.038]	0.302 [0.034]**
TECHSHARE	0.354 [0.043]**	0.565 [0.051]**	0.143 [0.057]*	0.868 [0.073]**	0.348 [0.078]**	0.27 [0.071]**
TECHTIME	-0.03 [0.004]**	-0.047 [0.005]**	-0.025 [0.006]**	-0.061 [0.005]**	-0.014 [0.005]**	-0.061 [0.004]**
ln employment	-0.01 [0.008]	-0.03 [0.010]**	-0.012 [0.010]	0.001 [0.014]	-0.143 [0.015]**	0.078 [0.013]**
lnAGE	-0.036 [0.013]**	0.027 [0.015]	0.088 [0.017]**	0.037 [0.023]	-0.035 [0.021]	-0.009 [0.019]
Constant	-0.566 [0.175]**	-1.525 [0.207]**	-0.872 [0.229]**	-4.228 [0.555]**	-1.032 [0.501]*	-4.078 [0.498]**
Total Observations	231319			125434		
Model chi-square	34393.73			21426.34		

Standard errors in brackets; * significant at 5%; ** significant at 1%

TABLE 3.4 NOTES: (a) The table is based on the 363,308 patents owned by 1273 unique Compustat firms with priority years 1981-2000, and issued between 1981-2004. The actual number of observations (356,753 patents) used in maximum likelihood estimation are the ones with complete data on all the included variables (b) Base class: no continuation ($j=0$); Combinations ($j=4$) included, but not reported. (c) Industry-, Patent Technology class & Priority-year effects included, but not reported.

Conclusion

The first chapter of this dissertation empirically evaluated the predictions of agency theory about the effect of imperfect information on contractual payment schemes in the market for ideas. The findings suggest that the relationship between information and the structure of contracts is more complicated than portrayed by theory, and is reflected in the prominence of alternative provisions such as minimum royalty and milestone payments. Future studies can investigate other settings, such as the movie industry, to confirm the generalizability of these findings. The chapter only investigated one means of organizing the trade of ideas. Important avenues for future work on this topic include: evaluating the implications of other information imperfections (for example, the inventor's appropriability problem) on transactions and institutions in the market for ideas, analyzing how contract structure influences performance, and comparing the choice and effectiveness of different modes (arm's-length contracts, alliances, and vertical integration) of organizing the exchange of ideas.

The second chapter showed that in the case of biomedical R&D, Congressional appropriators disguise transfers to research performers in their constituencies by supporting specific research fields and projects. The actions of congressmen to benefit their constituents are but one source of influence on the allocation of public funds. The allocations are also influenced by the lobbying activities of special interest groups, personal experiences of congressmen, the judgment of experts, and public opinion. The effects of these sources of influences can be correlated, and future empirical research can disentangle the effects of these varied influences. Future research on the influence of politics on the generation of ideas can also investigate whether other federal allocations considered unaffected by distributive politics are subject to cleverly concealed transfers, and estimate the deadweight losses associated with such indirect transfers.

The third chapter provided evidence that biomedical firms use the continuations process to lengthen the duration of patents protecting their most valuable ideas, while electronics and semiconductor firms use the process to augment the size of their patent portfolios. Still, several aspects of the continuations process remain less understood. What role do continuations play in other patent prosecution strategies such as: "submarine" patenting and "evergreen" patenting? More broadly, how do firms use the patent prosecution process to strategically disclose and protect their intellectual assets? The 1995 change in patent term, and the patent publication requirement enacted by the "American Inventors Protection Act" in November 2000, can be treated as "quasi-experiments" to identify and answer some of the above questions. I hope to pursue these avenues in future research.

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