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序文と要約
(Introduction and Summary in Japanese)

科学技術政策研究所では、平成16年2月 12日に「研究開発と『企業の境界』―バイオテクノロジーの産学連携と企業間提携」と題する国際コンファレンスを開催し、海外からお招きした著名な研究者5名を含む8名による講演をおこない、政策担当者、産業界、シンクタンク、大学研究者など計 200 名強のご参加を得た。翌 13 日には、これら海外からの研究者に加え、国内の研究開発戦略・科学技術政策研究者 16 名を招いて研究セミナーを開催し、7本の論文報告を中心に活発な討論をおこなった。本資料は、当日発表された論文を取りまとめたものである。

最初の論文は、小田切と中村健太氏によるもので「研究開発における企業の境界の決定要因―委託研究・共同研究・ライセンシングの日本企業データによる実証分析」と題されている。ここでは日本の製造業企業約 14,000 社のデータを用い、研究開発の外注の3形態である委託研究、共同研究、技術導入(ライセンシング・イン)の決定要因を分析している。ただし、サンプル企業の過半数が何らの研究開発活動もおこなっていないことに着目し、第1段階で、その企業が何らかの研究開発活動をおこなっているかどうかを識別し、おこなっている場合には、第2段階として、外注研究の個々の形態をどれだけおこなうかを決定するという2段階のモデル(ダブル・ハードル・モデル)を考え、それにより決定因を推定している。その結果、規模が大きく、研究開発集約的で、さらに垂直統合し多角化もしている企業ほど、また、特許による技術の専有が効果的な産業にいる企業ほど、外注研究をおこなうことが明らかにされている。

第2の論文は、長岡貞男教授による「研究開発と市場価値―専有可能性と先買い」である。ハーバード大学のグリリカス教授らは、トービンのqの対数値が無形資産と有形資産の比に依存するというモデルを示したが、筆者は、産業組織論的な観点から得られるプライス・コスト・マージンの決定式をトービンのq決定式に導入することにより、トービンのqの対数値は無形資産・有形資産比率ではなく、無形資産の大きさそのものに依存することを導き出した。そのうえで、日本の企業 2367 社・4年のパネルデータを用い、無形資産を研究開発費で近似して計測して回帰分析をおこなった結果、トービンのqの対数値が実際に、無形・有形比率ではなく無形資産額に有意に依存することを検証している。また、企業のマーケットシェアはトービンのqに正の効果を与えるものの、マーケットシェアと研究開発費の交叉項はむしろ負の係数を持つことから、マーケットシェアの高い企業が「先買い」という戦略的行動により高い収益を得ているという仮

説は否定されるとする。

第3の論文は、ロバート・ケネラー教授による「日本の企業とイノベーションの概観」で、特許データにより日米間でのイノベーションの構造の違いを分析している。特許庁の調査によれば、ゲノム・タンパク質関連技術においてアメリカ特許の 40%がベンチャー企業によるものであるのに対し、その比率は日本では12%、ヨーロッパでは6%に過ぎない。一方、大企業の特許の比率はアメリカでは 50%であるのに対し、日本でもアメリカでも 72%に達する。筆者は、このように日本の特許が大企業中心であることを、医療、エレクトロニクス、ナノテクノロジーなどの8分野について 1995 年、2003 年の日本特許とアメリカ特許を比較することにより確認している。

第4の論文は、スコット・シェーン教授による「専有可能性とイノベーションのタイミング—MIT における発明からの証拠」で、マサチューセッツ工科大学(MIT)の発明で 1980-1996 年に民間企業にライセンシングされた 805 件のデータを用い、企業がその後当該技術の商品化に成功したか、商品化を断念したかの確率を、ハザード率の手法を用いて実証分析している。その結果、特許の強さ(専有可能性)が高いほど、また特許の範囲(特許がカバーする分類の広さ)が広いほど、成功する確率が高いことが示されている。また、特許が古くなっていくに従い断念確率は当初低下していくが、特許が古くなると特許残存期間が短くなるために期待利益が低下し、このため一定時点から断念確率が上昇するというU字形の関係があることも発見している。

第5の論文は、元橋一之教授による「産学連携の経済分析—日本のイノベーション改革における新規技術型企業の役割」で、経済産業研究所が実施した産学連携についての企業への質問票調査結果を、企業データと結合して分析している。その結果、中小企業では若い企業ほど産学連携をする傾向があることが見られ、また、特許や生産性で計った成果に対する産学連携の効果を調べると、特許への正の効果、自社研究開発費の生産性に対する弾力性に対する正の効果など、一定の(ただし必ずしも統計的には有意でない)効果があることが確認されている。

第6の論文は、リー・ブランステッター教授による「学術的研究は産業イノベーションの急増に貢献しているか—特許引用からの証拠」で、アメリカ特許における文献への引用のうち、カリフォルニア州主要4大学の研究者の論文への引用に焦点を当てる。すると、こうした引用が 1980 年代から 90 年代にかけて急増しており、学術的な科学研究がイノベーションに与える貢献が大きくなっていること、ただしこの傾向はバイオテクノロジー関連で特に顕著であり、IT関連がそれに次ぐこと、特許と被引用文献の間に地域的な近接性が見られることなどがわかる。筆者はこのことから、大学研究から技術

革新への貢献は学術論文によるところが大であり、必ずしも大学における特許取得やTLOの活動によるものではないことを示唆している。

最後に、第7の論文は、ジョン・ウォルシュ教授による「金の鷲鳥は飛ぶか—公共的研究の産業研究開発への影響についての日米比較分析」で、1994 年に日本と米国でおこなわれたサーベイ調査(日本については科学技術政策研究所調査)を比較することにより、公共部門における研究の産業技術開発に対する貢献は日米でともに高く、どちらかといえば日本における方が高い傾向があることを示す。ただし、通信機器や自動車産業においてはむしろ米国の方が高い。こうした日米の差は、一部は企業規模、基礎研究比率、労働者配置転換頻度などで説明されるものの、それらをコントロールしても日米差が残っている。

以下、本資料では各報告者から提出された論文7編をそのままに収録しており、何らの編集作業をもおこなっていないことを付記する。また、以上の紹介における日本語タイトルおよび要約は本資料の編者(小田切)によるもので、論文筆者の校閲を受けたものではない。したがって、正確には原論文をお読みいただきたい。さらに、論文によっては他の形態(他機関からのディスカッションペーパーその他)でも刊行されているものがあることを付け加えておく。

最後に、同研究セミナーでご報告いただき、またこの調査資料への収録を快諾いただいた発表者、および研究セミナーに参加して活発な議論をおこなっていただいた参加者の各位に篤く御礼申し上げる。

科学技術政策研究所第1研究グループ
総括主任研究官
小田切 宏之

Preface in English

On 12 February 2004, the National Institute of Science and Technology Policy (NISTEP) held an International Conference on "R&D and the Boundaries of the Firm – University-Industry Collaborations and Research Alliances in Biotechnology." With presentations by eight speakers including five distinguished scholars from abroad, the Conference was successful with the participation of more than two hundred people ranging from policy makers, industry people, and research institution members to university academics.

On the following 13 February, NISTEP invited these five scholars from abroad as well as sixteen scholars in Japan to have a Research Seminar on "R&D Strategy and Science and Technology Policy." Seven papers were presented, followed by intense but friendly discussions. This volume is compiled from all the seven papers presented at this seminar.

We note that the seven papers are included here without our making any editing and that many of the papers have been (or will be) printed elsewhere in journals, working papers, and such. We wish to thank the authors of these papers for making presentations at the NISTEP Research Seminar and for allowing us to reproduce the papers in this manner. We also thank all the participants of the seminar for lively and stimulating discussions.

Hiroyuki Odagiri

Director, First Theory-Oriented Research Group

National Institute of Science and Technology Policy

NISTEP Research Seminar
"R&D Strategy and Science and Technology Policy"

Date: 13 February 2004 (Friday)
Venue: Tokyo International Forum (Meeting Room, G610),
Language: English

Program

10:00-10:50 ***Session 1: Industrial R&D***

- Hiroyuki Odagiri (NISTEP and Hitotsubashi University), " R&D Boundaries of the Firm: An Estimation of the Double-Hurdle Model on Commissioned R&D, Joint R&D, and Licensing in Japan " (with Kenta Nakamura)

10:50-11:10 Coffee Break

11:10-12:50 ***Session 1 – continued***

Chair: Tomohiro Ijichi (NISTEP and Hitotsubashi University)

- Sadao Nagaoka (Hitotsubashi University), " R&D and Market value: Appropriability vs. Preemption "
- Robert Kneller (University of Tokyo), "Japan's Corporate and Innovation Landscape"

12:50-14:00 Lunch

14:00-15:40 ***Session 2: University-Industry Collaborations***

Chair: Fumio Kodama (Shibaura Institute of Technology)

- Scott A. Shane (Case Western Reserve University), "Appropriability and the Timing of Innovation: Evidence from MIT Inventions" (with Emmanuel Dechenaux, Brent Goldfarb, and Marie C. Thursby)
- Kazuyuki Motohashi (University of Tokyo), "Economic Analysis of University-Industry Collaborations: The Role of New Technology Based Firms in Japanese National Innovation Reform"

15:40-16:10 Coffee Break

16:10-17:50 ***Session 3: The Impact of Academic and Public Research***

Chair: Hiroyuki Odagiri (NISTEP and Hitotsubashi University)

- Lee Branstetter (Columbia University and Hitotsubashi University), "Is Academic Science Driving a Surge in Industrial Innovation?: Evidence from Patent Citations"
- John P. Walsh (University of Tokyo), "Does the Golden Goose Travel?: A Comparative Analysis of the Influence of Public Research on Industrial R&D in the U.S. and Japan" (with Wesley M. Cohen)

List of Participants

(alphabetical order)

<Invited Guests> *<NISTEP>*

Name	*Affiliation*	*Name*	*Affiliation*
Arora, Ashish	Carnegie Mellon U.	Hirano, Yukihiro	Deputy Director General
Branstetter, Lee	Columbia U. & Hitotsubashi U.	Ijichi, Tomohiro	1 Res. & Hitotsubashi U.
Chuma, Hiroyuki	Hitotsubashi U.	Imamura, Tsutomu	Director General
Degami, Satomi	Recombinant Capital, Inc.	Iwasa, Tomoko	1 Res.
Doi, Noriyuki	Kwansei Gakuin U.	Koga, Tadahisa	1 Res.
Fujimura, Shuzo	Hitotsubashi U.	Kondo, Masayuki	Director, 2 Res. & Yokohama National U.
Hughes, Alan	Cambridge U.	Kuwahara, Terutaka	STFC
Kodama, Fumio	Shibaura Institute of Technology	Nakamura, Kenta	1 Res. & Hitotsubashi U.
Kneller, Robert	U. of Tokyo	Odagiri, Hiroyuki	Director, 1 Res. & Hitotsubashi U.
Motohashi, Kazuyuki	U. of Tokyo		
Nagaoka, Sadao	Hitotsubashi U.		
Nakamura, Yoshiaki	Ministry of Economy, Trade, and Industry		
Nelson, Richard R.	Columbia U.		
Okada, Yosuke	Hitotsubashi U.		
Orsenigo, Luigi	Bocconi U.		
Shane, Scott	Case Western Reserve U.		
Shinjo, Koji	Kobe U.		
Sunami, Atsushi	National Graduate Institute for Policy Studies (GRIPS)		
Wada, Tetsuo	Gakushuin U.		
Wakasugi, Ryuhei	Yokohama National U.		
Walsh, John	U. of Tokyo & U. of Illinois		
Yasuda, Hideto	Edogawa U.		

1 Res. = First Theory-Oriented Research Group
2 Res. = Second Theory-Oriented Research Group
STFC = Science and Technology Foresight Center

R&D Boundaries of the Firm:

An Estimation of the Double-Hurdle Model on

Commissioned R&D, Joint R&D, and Licensing in Japan

Kenta Nakamura* and Hiroyuki Odagiri†

February 2004

Paper presented at the NISTEP Research Seminar, "R&D Strategy and Science and Technology Policy," 13 February 2004. This is a shortened and slightly revised version of "Determinants of R&D Boundaries of the Firm: An Empirical Study of Commissioned R&D, Joint R&D, and Licensing with Japanese Company Data," NISTEP Discussion Paper No. 32. The current version was also printed as COE/RES Discussion Paper, No. 17, Hitotsubashi University. Any opinion expressed in this paper is the authors' alone and does not represent any of the institutions the authors are affiliated with. An earlier version was presented at NISTEP Internal Seminar, Hitotsubashi University Workshop, and the 2003 Spring Meeting of Japanese Economic Association. We thank R. Wakasugi and other participants for helpful comments.

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Abstract

This paper studies the determinants of R&D boundaries of the firm, namely, the firm's choice between performing R&D in-house *versus* procuring it from outside. We separate three modes of *procured R&D* – commissioned R&D, joint R&D, and technology acquisitions (i.e., licensing-in) – and, using the data of about 14,000 manufacturing firms in Japan, estimate the determinants of each mode. Two novelties are incorporated in this analysis. First, because the majority of the sample firms do not perform any R&D activity at all, we estimate a modified double-hurdle model in which the first hurdle determines whether the firm performs any R&D at all and the second hurdle determines whether (and how much) it performs each mode of procured R&D. Second, we employ both firm variables and industry variables (weighted with the firm's sales composition) to test the two major theories of the boundary of the firm, that is, the transaction cost theory and the capability theory. The results generally support these two theories: the estimated positive effects of firm size, in-house R&D intensity, diversification, and vertical integration support the hypothesis that capability is needed for procured R&D, while the estimated positive effect of the index of appropriability with patents supports the hypothesis that appropriability reduces transaction costs.

JEL Classification Code: D23, L22, O31

Keywords:

Firm Boundaries, Commissioned R&D, Joint R&D, Licensing, Transaction Cost, Capability

1 Introduction

Traditionally, the issue of the boundary of the firm has been discussed in relation to make-or-buy decisions in a vertical chain of production. How much supply of materials and parts is (and should be) integrated has been at the center of both theoretical and empirical studies on the boundary of the firm.

This issue has become a critical decision in the firm's research and development (R&D) strategy as well. With technologies becoming more science-based and complex, and with competition becoming more intensive on a global scale, it is now difficult for any firm to develop all the technologies by themselves. More and more, firms depend on scientific knowledge generated in universities, technologies acquired from other firms, and alliances with other firms, universities, and research institutes. This tendency is particularly strong with such high-tech industries as pharmaceuticals, chemicals, electronics, and automobile (e.g., Hagedoorn, 1993, 2002). In these and other industries, how much R&D should be performed in-house and how much R&D should be procured from outside have become one of the central strategic decisions in R&D management.

Following the pioneering work of Teece (1986), a number of studies have investigated the determinants of R&D boundaries of the firm. The results have been mixed. For example, regarding the effect of in-house R&D or patents (or its intensity) on variables of R&D alliances or collaborations, Arora and Gambardella (1990, 1994) and Veugelers (1997) found a significant positive effect, suggesting complementarity between internal R&D and external R&D. However, Kleinknecht and Reijnen (1992) found the effect to be insignificant except for collaborations with foreign research institutes. Furthermore Rocha (1999) found the effect of R&D intensity on the ratio of joint patent applications to be negative, though insignificant.

In this paper, we aim to analyze such determinants, using a comprehensive data of manufacturing firms in Japan. Our study is unique in several respects. First, whereas most of the existing studies were confined to particular industries, such as biotechnology, or to a small number of firms, we use a large data set of approximately 14,000 Japanese firms that cover all the manufacturing industries. Second, we apply a double-hurdle model (Cragg, 1971) in order to investigate the two-step decisions, that is, whether or not the firm should perform any R&D at all and, if it should, how much it should spend for external R&D resources. Third, to take into account the fact that firms procure external R&D resources through diverse means, we separate commissioned R&D, joint R&D, and technology acquisitions. Fourth, as the determinants of these means of procured R&D, we examine not only firm characteristics, such as firm size, R&D intensity, diversification, vertical integration, ownership, and cash flow, but also technological and industrial characteristics. The latter are represented by the indexes of appropriability by patents, the extent of information flow, and innovation speed, which were derived from the questionnaire study of Goto and Nagata (1996). These variables, we will argue, are closely related to the two major theories of the boundary of the firm – the transaction cost theory of Williamson (1975, 1985) and the capability theory of Penrose (1959), Nelson and Winter (1982), and others.

The remainder of the paper is organized as follows. In the next section, we define three major forms of procured R&D – commissioned R&D, joint R&D, and technology acquisitions – and discuss the fundamental differences among them. In Section 3, we discuss the above-mentioned two theories of the R&D boundary of the firm. In Section 4, we explain the data source and the variables on procured R&D to be used as the dependent variables in our regression. In Section 5, we explain our double-hurdle model. In Section 6, we explain the independent variables, together with the hypotheses on their effects to procured R&D and, in Section 7, we present the estimation results. Finally, Section 8 summarizes our findings and concludes the paper.

2 In-house R&D versus Procured R&D

'In-house R&D' (IRD) refers to the activity of the firm whereby it sets up and fulfills a research project within itself, by employing necessary resources, such as researchers, research materials, and equipment. Alternatively, it can procure a part of the R&D activity from outside. In this paper, we investigate three modes of what we call 'procured R&D'; commissioned R&D, joint R&D, and technology acquisitions. They differ in important ways[1].

[1]Some authors (e.g., Audretsch et al., 1996, and Bönte, 2003) used the terms, 'internal R&D' and 'external R&D', in place of 'in-house R&D' and 'procured R&D'. We prefer the term, 'procured R&D', to 'external R&D' because external R&D can be worthless unless the firm makes deliberate efforts to *procure* it, by making sacrifices in the form of payments or the allocation of its human and other resources. Although the firm may also enjoy the benefit of external R&D without payment through *spillovers*, they are not the subject of the present study: for spillovers, see Griliches (1992).

Technology acquisitions (TA) are the purchase of technologies through, most commonly, licensing-in of patents. Non-patented technologies, such as knowhow and consultancy, may be also purchased. A salient feature of TA is that the technology to be traded has been already invented by the time the contract is made; therefore, uncertainty is lower as to the outcome from the contract and the object of the contract can be more clearly defined. That is, the 'predictability' of the outcome is higher and so is the 'definability' of the work to be conducted to fulfill the contract (Odagiri, 2003)[2].

Both predictability and definability are lower in *commissioned R&D* (CRD) and *joint R&D* (JRD), or *R&D alliances* as they are collectively called, because they need to be contracted before the actual R&D process is to be started. CRD and JRD differ with regard to the way the participants are involved and the outcomes are shared between them. In JRD, the R&D work is to be shared by the participants, each of them contributing R&D funds and/or R&D personnel whereas, in CRD, the R&D work is basically the responsibility of the commissioned party. The commissioning party provides R&D funds as stipulated by the CRD contract and usually receives the entire right to the R&D outcome.

Incomplete definability and low predictability can cause information asymmetry among the partners and, thereby, moral hazards. For instance, in CRD, the commissioned party (say, Firm B) may realize during the course of the commissioned research that the chance of coming up with an invention is actually much lower than was predicted at the time of the contract. However, if the commissioning party (Firm A) is unaware of this fact, B may be tempted to conceal it so that it can keep receiving the research fund from A. In JRD, a free-rider problem may occur because each participating firm has an incentive to minimize its contribution and yet to receive information fully from the project and the partners. Thus, neither CRD nor JRD is free from transaction costs as broadly defined. Yet, both are useful in the exploitation of capabilities held by other partners, which provide a strong motivation for procured R&D. It is thus suggested that we need to inquire into the issues of transaction costs and capabilities to study the R&D boundaries of the firm.

[2]Technology may be also acquired through acquisition of patent-holding companies (Huber, 1991; Ahuja and Katila, 2001). In the US, M&As for this purpose are common particularly in IT industries (Inkpen, Sundaram, and Rockwood, 2000). In this paper, we do not discuss such M&As because, firstly, M&As may be motivated by organizational as well as technological purposes and, secondly, M&As are relatively infrequent in Japan (Odagiri, 1992).

3 Two Main Theories

3.1 The Transaction Cost Theory

Probably the best-known theory on the boundary of the firm is the *transaction cost theory*, advocated by Williamson (1975, 1985). Under uncertainty, complexity, asymmetric distribution of information, and bounded rationality, market transactions can be costly particularly because the participants may behave in an opportunistic fashion. Generally, these transaction costs make in-house activities more advantageous than market transactions. However, integrating the activities in-house can be also costly because of reduced competitive pressure from the market, influence costs, and other costs from integration. The firm, therefore, needs to determine the best allocation between in-house R&D and procured R&D with due consideration for the balance between integration costs and transaction costs.

This balance depends on many factors but here we focus on two. The first is the extent that required tangible and intangible assets are transaction-specific. If they are transaction-specific, few suppliers are willing to invest in them for fear of the buyer's hold-up. Thus, in the case of R&D, if the R&D project requires investment in specific equipment or other assets, it is more likely carried out in-house than being procured from outside.

The second is the extent of definability and enforceability of property rights. In the transaction of intangible assets such as technology, it is not easy to specify in the contract the range of technology to be transacted and each party would be tempted to interpret it in a way more favorable to them. In a commissioned R&D, for instance, the commissioned party (a firm, university, research institute, etc.) would try to limit the range of technology to be handed over to the commissioning party. The intellectual property rights system, such as the patent system, helps the parties to resolve this difficulty because the range of relevant technology is specified in a patent. This tendency is most applicable in the licensing of patents because, by referring to patent numbers, contracts can be well defined. Even in commissioned or joint R&D, one can more easily write and enforce contracts by stipulating that the outcome be patented and handed over from the commissioned party to the commissioning party or to be shared among the partners.

In reality, however, patents may not allow the inventor to appropriate profits fully from the invention and the extent of such appropriability is known to vary across industries (Cohen et al., 2000; Goto and Nagata, 1996; Levin et al., 1987). We will therefore investigate the effect of appropriability in our empirical analysis.

3.2 The Capability Theory

The second theory to explain the boundary of the firm is the *capability theory*, which originates from Penrose (1959) who stressed the importance of viewing the firm as a collection of physical and human resources, and was developed further by Nelson and Winter (1982) and others, and applied, for instance, to discuss the Japanese industrial development by Odagiri and Goto (1996). The theory has been also called the theory of a resource-based view of the firm (Wernerfelt, 1984), organizational capability (Chandler, 1990), dynamic capability (Teece, Pisano, and Shuen, 1997), or core competence (Prahalad and Hamel, 1990), with slightly different emphases and purposes.

It takes time and costs for the firm to create and enhance its tangible and intangible assets and hence its capabilities. The firm can of course develop its capabilities through investment and learning. Yet, the speed and direction of this development are constrained and influenced by not only the firm's social and economic environment but also the volume and composition of its current assets and the history of its development. As a result, the development is bound to be path-dependent.

The firm can fulfill a certain task cheaper and faster if it procures it from an outside party who possesses more of the necessary capabilities than when it conducts it within itself. In other words, the decision on the firm's boundary is dependent on the relative level of in-house capabilities versus outside capabilities.

However, one needs to note the dynamics of capabilities. If a certain activity is performed within the firm, it can learn from the experience and enhance its capabilities. Hence, even if the cost of doing so is higher in the short run, the expected long-run cost reduction may be large enough to offset the short-run cost. On the contrary, if the firm depends on outside resources, its capabilities will gradually become obsolete, causing the firm to lose not only the capability to perform the activity in-house but also the capability needed to evaluate the procured goods and services, monitor the suppliers, and bargain with potential suppliers and partners. In short, it will also lose its 'absorptive capacity'.

Therefore, it is indispensable for the firm to maintain a certain level of capability through in-house R&D[3]. It should not consider the relative merit of in-house R&D versus procured R&D merely from the comparison of current costs. The capability theory teaches us that it needs to take a dynamic and broad view in determining the boundary of the firm.

4 Data and the R&D Variables

We now proceed to our empirical analysis on the determinants of commissioned R&D, joint R&D, and technology acquisitions (i.e., licensing-in). We use unpublished firm-level data from the *Basic Survey cf Business Structure and Activities* (hereafter BSA): see Appendix 1 for the detail of this data. BSA is unique in that it asked the firms to provide information on not only their in-house R&D but also the above-mentioned three modes of procured R&D. However, the question items vary slightly from year to year and all of the three were included only in the 1998 BSA report, which covers the data of 1997 accounting year (April 1997 to March 1998 for most firms). Thus, the data for all the variables in the following are taken from this 1998 report, except those variables representing industrial and technological characteristics to be discussed later.

Our sample consists of 14,070 manufacturing firms in the survey. Among these, 6,281 (44.6%) reported to have expended for in-house R&D and, including commissioned and joint R&D and licensing-in, 6,648 (47.2%) reported to have made some form of R&D activities. We will use this information in the following analyses.

There are four R&D-related variables:

IRD_i = the amount (in million yen) of R&D expenditures firm i used in-house.

CRD_i = the amount (in million yen) of R&D expenditures that firm i commissioned to any of the organizations outside the firm.

JRD_i = the number of partners (besides the firm in question) in joint R&D projects that firm i participated[4].

[3]In fact, in the questionnaire study, we conducted earlier (Odagiri, Koga, and Nakamura, 2002), many Japanese bio firms raised the full utilization of internal resources and the need to nurture them as the major reasons for not making R&D alliances even when there are opportunities for such alliances.

[4]BSA requires that, in any joint R&D, the participants share R&D activities, share the outcomes, and exchange a contract. It is thus separate from commissioned R&D or subcontracting.

TA_i = the amount of payment firm i made for licensing-in of patents (whether the licensing contract was made during the year or earlier)[5].

CRD_i includes R&D expenditures commissioned to the firm's affiliates (of which the firm owns more than 20 percent of the share), its majority-controlling parent (who owns more than 50 percent of the firm's share), other firms, universities, and government research institutes, inside or outside of Japan. BSA reports the proportion of CRD_i to its affiliates and the parent; hence, we can calculate the following two:

$CRDI_i$ = R&D expenditures that firm i commissioned to its affiliates or the parent (to be called 'in-group commissioned R&D').

$CRDN_i$ = R&D expenditures that firm i commissioned to any party outside of the group ('non-group commissioned R&D')[6],

where, of course, $CRD_i = CRDI_i + CRDN_i$.

In-group commissioned R&D, one may hypothesize, is a form of *quasi*-internal R&D rather than procured R&D and, hence, the determinants can differ from those for non-group commissioned R&D. We will test this hypothesis.

Table 1 gives the descriptive statistics for the variables. Among the 14,070 sample firms, 1,315 (9%) commissioned R&D. Of the total commissioned R&D, 79 percent went to non-group. Only 296 (23%) of the 1,315 firms commissioned R&D to in-group. Among these firms, however, nearly two thirds of the commissioned R&D went to in-group (not reported in the table). These facts imply two things. First, more than three quarters of the firms making commissioned R&D are commissioning only to non-group and more than three quarters of commissioned R&D expenditures went to non-group. However, there are a number of firms who are heavily commissioning R&D to their affiliates or the parents. Presumably, many of these firms have hived-off their R&D departments as separate subsidiaries[7], or they may have a specialist R&D company within the group.

The proportion of firms conducting joint R&D or technology acquisition is smaller than that of commissioned R&D at, respectively, 6.8 percent and 5.9 percent. However,

[5] TA_i also includes payments for knowhows that accompany patents.

[6] $CRDN_i$ still includes R&D commissioned to firms for which firm i owns less than 20 percent of the share.

[7] That many Japanese firms hive-off some of their divisions has been discussed in Odagiri (1992).

as a proportion to the 6,648 firms with positive in-house and/or procured R&D, the percentages (not reported in the table) increase to 20 (CRD_i), 14 (JRD_i), and 13 (TA_i).

5 The Double-Hurdle Model

CRD_i, JRD_i, and TA_i equal to zero for more than ninety percent of the sample. As is well known, when the dependent variable is constrained to be non-negative and takes the value of zero in a large portion of sample, the OLS estimates are biased and the common research strategy is to apply a left-censored (at 0) Tobit model (Tobin, 1958). We basically follow this strategy. In addition, since we know that a number of firms not only have not made the procured R&D but, actually, have not made any R&D activity at all inside or outside of the firm, we wish to utilize this information.

Put differently, we may approach the issue of the R&D boundaries of the firm as a sequence of R&D decisions. Firstly, should the firm expend for any R&D activity at all? If the answer is yes, then, secondly, how much should it expend in-house and how much by procurement and, if procurement, how much should it expend for each mode of procured R&D?

Let us, for the moment, consider only commissioned R&D as a means of procured R&D. Then, one can estimate a two-stage model. The first stage determines if IRD_i + $CRD_i > 0$. If it is, then the second stage determines if $CRD_i > 0$ and, if it is, how much expenditures should be made for it. These two stages have to be estimated jointly. For this purpose, we apply a double-hurdle model, which was originally suggested by Cragg (1971) as a generalized form of the Tobit model. In Cragg's original model, two hurdles refer to the following: "First, a positive amount has to be desired. Second, favorable circumstances have to arise for the positive desire to be carried out" (Cragg, 1971, p. 831). In our case, the first hurdle is to have positive $IRD_i + CRD_i$ or, equivalently, to have $ICRDD_i = 1$ where $ICRDD_i$ is a dummy variable that equals one if and only if $IRD_i + CRD_i > 0$, and the second hurdle is to have a positive CRD_i. Figure 1 shows the flow chart for this model.

These two equations, that is, the first-hurdle equation (that determines $ICRDD_i$) and the second-hurdle equation (that determines CRD_i), are jointly estimated by means of the maximum likelihood method (see Appendix 2 for the derivation of the likelihood function). In this maximum likelihood estimation, the maximand includes the terms related to the second-hurdle equation only for samples with $ICRDD_i = 1$. Also, the covariance between the residuals of the two equations are taken into account .

When other modes of procured R&D, namely, joint R&D and technology acquisitions, need to be considered, it is ideal to have the choice among the three modes simultaneously incorporated into the second hurdle. Unfortunately, we cannot do so for want of a 'total' R&D variable, in addition to the complexity of maximum likelihood computation. As mentioned above, IRD_i, CRD_i, and TA_i are in monetary units but JRD_i is the number of participants. Hence, the sum of these numbers is meaningless. Besides, TA_i is the amount the firm paid for acquired technologies during the year. Since this payment is usually composed of fixed initial payment and running royalty, with the latter being commonly determined as a fixed percentage of sales, the amount can fluctuate violently from year to year. Also, the firm may keep paying for many years after the actual technology acquisition took place. Consequently, adding TA_i to IRD_i and CRD_i need not provide a good measure of the current R&D activity.

For these reasons, we estimate the double-hurdle model separately for each mode of procured R&D. For the JRD_i and TA_i equations, however, a new variable RDD_i is used in place of $ICRDD_i$ in the first-hurdle, where RDD_i equals one if any of IRD_i, CRD_i, JRD_i, and TA_i is positive and zero otherwise (i.e., when none of these four is non-zero), in order to include several firms who have not expended for in-house or commissioned R&D and yet participated in joint R&D or made payments for technology acquisitions.

6 Independent Variables and Hypotheses

There are two types of independent variables, those for firm characteristics and those for industrial characteristics. We now discuss them together with our hypothesis on the signs of the coefficients. The definitions of independent variables and their basic statistics are shown in Table 2.

6.1 Firm Characteristics

R&D intensity

This variable appears as an explanatory variable only in the second hurdle. Cohen and Levinthal (1989) argued that, with R&D, the firm can enhance its absorptive capacity that is needed to exploit external knowledge efficiently. Also, a more R&D-intensive firm will be more alert to outside R&D opportunities and will have more knowledge on potential alliance partners and the technologies to license. It is thus hypothesized that R&D intensity has a positive impact on procured R&D, where R&D intensity ($RDINT_i$) is defined by the ratio of in-house R&D expenditure to sales. Earlier empirical results of Arora and Gambardella (1990, 1994) and Veugelers (1997), and more recently, Bayona et al. (2001) support this hypothesis[8].

Some authors, on the contrary, suggested that in-house R&D and procured R&D are substitutes because the firm can fulfill a certain R&D task either by making it by itself or by commissioning it from outside. Pisano (1990), for instance, found that biotechnology firms that have accumulated technical knowledge in-house are less likely to rely on external knowledge. If this were the case, then, the firm with active in-house R&D would rather not procure R&D from outside and, consequently, we should expect a negative coefficient for $RDINT_i$. As will be shown later, however, our estimated coefficient is positive. Hence, in the sense that procured R&D increases with in-house R&D, the two appear complementary than substituting, although we have not rigorously tested the causality as in Colombo and Garrone (1996).

Size

The relationship between firm size and R&D investment has been studied by many, often in conjunction with Schumpeter (1942). Although their results disagree as to whether a larger firm expends for R&D more than proportionally, they agree that "the

[8]A good question is whether only in-house R&D contributes to absorptive capacity or procured R&D also contributes. If it is the process of R&D being made within the firm that contributes to the formation of absorptive capacity, then, in-house R&D intensity ($RDINT_i$) is more likely to matter. If, on the other hand, invented technologies, whether invented in-house or not, are the sources of absorptive capacity, then, total R&D intensity ($TRDINT_i$) is more likely to matter. Actually, this choice hardly matters because, on average, in-house R&D expenditure accounts for 94 percent of total R&D expenditure and the correlation coefficient between $RDINT_i$ and $TRDINT_i$ reaches 0.98. We confirmed this fact by using $RDINT_i$ and $TRDINT_i$ as alternative explanatory variables and obtaining basically the same estimation results. It may be also argued that R&D stock, that is, an accumulated value of R&D expenditures with obsolescence taken into account, is a more accurate measure of the firm's technological capabilities than R&D expenditure of a single year. The major reason that we did not use R&D stock is the lack of continuous time-series R&D data for many of the sample firms. Rather than reducing the sample size by restricting the sample to those for which the time-series R&D data is available, we decided to use R&D flow data and maintain the sample size as large as possible.

likelihood of a firm reporting positive R&D effort rises with firm size" (Cohen and Klepper, 1996). Therefore, we hypothesize that the effect of size on the dummy variable, $ICRDD_i$ or RDD_i, in the first hurdle is positive.

In the second hurdle, it is difficult to predict the effect of firm size on the frequency of procured R&D. On the one hand, as Granstrand et al. (1997) and Patel and Pavitt (1997) emphasized, large firms may be technologically diversified and well-endowed, thereby having a better knowledge and better access to potential external partners. On the other, they may be able to achieve scale and scope economies with their in-house R&D, thus feeling a lesser need for procuring R&D resources. For instance, Veugelers (1997) and Veugelers and Cassiman (1999) found a negative relationship between firm size and R&D cooperation to argue that, because small firms can neither undertake a large-scale research nor undertake a number of research projects simultaneously, economies of scale and scope cannot be achieved, making R&D alliances more attractive to these firms.

A cursory look at our data suggests that the first hypothesis is more likely to hold; for instance, the proportion of firms making commissioned R&D is 20 percent among the firms with 300 employees or more but only 6 percent among smaller firms. We thus predict a positive relationship between $LSALE_i$, the natural logarithm of sales (including oversea sales), and procured R&D. This positive relationship may also come from the fact that CRD_i, JRD_i, and TA_i are all measured as numbers, such as expenditures and the number of partners, and not ratios. Hence, a positive association between $LSALE_i$ and these variables need not mean that a larger firm expend on procured R&D more than proportionately[9].

Vertical Integration

The extent of vertical integration (VI_i) is measured by the ratio of value-added to sales, on the presumption that a less integrated firm will expend a larger proportion of sales in the procurement of parts and components, thus having a smaller value-

[9]We found, however, that the estimated coefficients remain positive and significant (except that for JRD_i) even when CRD_i, JRD_i, and TA_i are measured as intensities (i.e., as ratios to sales): see Nakamura and Odagiri (2003). Therefore, commissioned R&D and technology acquisitions in fact tend to increase more than proportionately with size.

added/sales ratio.

A more vertically integrated firm, one may hypothesize, should feel a stronger need for R&D because it has to maintain technological competence in all stages of the vertical chain. Then the effect of VI_i on the probability of conducting R&D would be positive in the first hurdle. The effect of double-counting has to be also taken into account. Because costs of R&D personnel and capital are included in the firm's value added, an R&D-performing firm is likely to have a higher value-added/sales ratio. Again, we would expect a positive effect of VI_i in the first hurdle.

Such double-counting is unlikely to occur in the second hurdle because commissioned R&D will be carried out within the commissioned party utilizing its employees and capital. It may occur in the case of joint R&D as long as the firm's researchers participate in the joint R&D but, since the expenditure on joint R&D is tiny in comparison to in-house R&D, the effect of double-counting must be too small to change the sign of the coefficient of VI_i in the second hurdle.

Other effects of VI_i on procured R&D can be mixed. On the one hand, VI_i may be interpreted as a proxy variable indicating that the firm's environment is more favorable to integration than market transactions. Transaction costs may be higher because of higher asset specificity, a larger sunk cost, or a larger probability of hold-ups. Ideally, a direct measure of these costs is more desirable than VI_i. For instance, Ulset (1996) found that potential sunk costs in R&D are positively related to vertical integration (i.e., in-sourcing) of R&D by using R&D project-level data for the IT industry. Such data is unavailable in Japan and, assuming that VI_i is positively correlated with the extent of transaction costs, we may hypothesize that firms with higher VI_i are more likely to undertake R&D internally.

On the other hand, from the viewpoint of absorptive capacity, a vertically integrated firm may have a higher capability to perform alliances and to absorb their outcomes, owing to its experience of having had business relations with firms of vertically diverse activities and culture, its understanding of technologies at vertically different stages, and its wider knowledge of potential partners. Then, firms with higher VI_i would be more likely to engage in procured R&D.

In consequence, the transaction cost theory and the capability theory would predict the sign of the coefficient of VI_i on CRD_i, JRD_i or TA_i differently.

Diversification

The extent of diversification, DIV_i, is measured by one minus the square root of Herfindahl index (the sum of the squares of the proportions of the firm's sales of three-digit products). In the first hurdle, its effect on the probability of R&D is expected to be positive. Nelson has earlier argued in his now classic paper (Nelson, 1959) that the outcome of R&D is inherently uncertain and this uncertainty makes diversified firms more advantageous in the commercialization of invented technologies. Hence, a more diversified firm will likely undertake R&D with a higher probability, although empirical results on the relationship between diversification and the level of R&D investment are not unanimous: McEachern and Romeo (1978) and Jovanovic (1993) found a positive correlation but a series of studies by Hoskisson and others (e.g., Hoskisson et al., 1993) found a negative relation.

In the second hurdle, the capability theory can suggest either a positive or negative effect of DIV_i. On the one hand, a more diversified firm may have a lesser need to depend on outside partners in pursuing R&D in non-core fields, suggesting a negative effect of DIV_i on procured R&D. On the other hand, a more diversified firm may have a broader absorptive capacity, which helps the firm to procure R&D efficiently, suggesting a positive effect of DIV_i. For instance, by applying Nelson's argument to procured R&D, we may say that a more diversified firm should be able to utilize the uncertain outcome from joint R&D more effectively. Assuming that the latter effect is dominant, we hypothesize that DIV_i will have a positive coefficient in the second hurdle. This assumption, we trust, is plausible because our measures of procured R&D are the expenditures or numbers and not intensity, and because, even though the first argument suggests that a more diversified firm will procure proportionally fewer of its R&D from outside, it need not imply that such a firm will procure a smaller amount of R&D from outside.

Cash Flow

R&D investment is usually riskier than other forms of investment. As a result, under information asymmetries between firms and investors (or lenders), the firm can more easily invest in R&D when it has an abundant cash flow. Thus, Himmelberg and Petersen (1994) found in small high-tech firms that R&D expenditure is sensitive to cash flow. Also, Goto et al. (2002) found that the ratio of cash flow to assets has a positive effect on the R&D-asset ratio in both large and small Japanese manufacturing firms. We thus expect that a firm with more abundant cash flow is more likely to perform R&D; that is, the ratio of cash flow to sales, CFS_i, will have a positive coefficient in the first hurdle.

The same argument is applicable to commissioned and joint R&D provided that, because of the low predictability and definability as discussed in Section 2, such investment is riskier than investment in tangible assets and is also less suitable for collateral. This argument may be less applicable to technology acquisitions (TA_i) because, usually, technologies to be licensed have been already invented and hence their predictability and definability need not be low. We thus predict CFS_i to have a positive impact on CRD_i and JRD_i but not necessarily on TA_i.

One may alternatively argue that joint R&D is preferred to in-house R&D when the firm wishes to share the cost and risk of the R&D project with the partners. According to this hypothesis of cost- and risk-sharing motivations for joint R&D, the firm may opt for joint R&D when it is short of cash flow, implying a negative coefficient of CFS_i on JRD_i and, perhaps to a lesser extent, CRD_i. Kleinknecht and Reijnen's (1992) finding supported this argument among joint research between domestic firms.

Parent Control

PC_i is a dummy variable indicating the presence of a parent company. It equals one if and only if the firm is owned a majority share by its parent company. Wakasugi (1999) found a higher R&D intensity among firms owning subsidiaries and argued that there is a division of labor between parent companies and subsidiaries, with the former conducting most of R&D. According to this argument, if the firm is a subsidiary (and unless it is a subsidiary established for the purpose of R&D like Honda's Honda R&D Co., Ltd.), it is presumably less likely to undertake R&D activity at all (in the first hurdle) and less likely to undertake procured R&D (in the second hurdle) because the decisions on alliances and licensing will be also concentrated in the parent company. One may therefore hypothesize that PC_i should have a negative coefficient in both the first and second hurdles.

However, regarding $CRDI_i$ (in-group commission of R&D), the discussion is more complex because subsidiaries may commission R&D to the parents or other in-group firms. In fact, we found that 46 percent of the firms commissioning R&D in-group are parent-controlled (i.e., $PC_i = 1$) and the percentage is significantly higher than that of firms not commissioning R&D in-group. Hence, the aforementioned hypothesis of a negative effect of PC_i is unlikely to apply to $CRDI_i$ and we would instead expect a positive effect.

6.2 Industrial and Technological Characteristics

R&D strategies depend not only on firm characteristics but also on industrial and technological characteristics. In this paper, we employ three variables representing these characteristics – appropriability, information flow, and innovation speed. They are derived from Goto and Nagata (1996), who sent questionnaires to 1,219 Japanese R&D-performing manufacturing firms with capitalization over one billion yen, with 643 responses, and reported industrial averages in their paper[10]. These variables, therefore, are constructed from the responses of big firms and there remains a possibility that they do not accurately describe the environment of smaller firms that occupy the majority of our sample.

Since our empirical study is made at the firm level, we may use either the data of each firm's responses or industrial averages. One may argue that firm-level data are more appropriate because even if firms belong to the same industry, the environment can be heterogeneous among firms. One may, on the other hand, argue that firm-level data are susceptible to the firms' subjective evaluation and prefer industry-level data, which is less dependent on each firm's individual opinion. Partly for this reason and partly for a practical reason that the sample size of Goto and Nagata's survey is much smaller than that of BSA and hence firm specific data are not available to all the BSA sample firms, we use industrial data. However, to take into account the effects of inter-firm differences, we generated firm-specific variables by computing the weighted averages of industrial data (basically at the three-digit Japanese SIC level) with the sales composition of each firm as the weights. Thus, even though these variables are

[10]This survey was conducted in 1994 in conjunction with the Carnegie Mellon survey, which is an expansion and update of the Yale Survey (Levin et al., 1987): see Cohen, Goto, Nagata, Nelson, and Walsh (2002) and Cohen, Nelson, and Walsh (2000, 2002). Some of the data are not reported in the report and we thank A. Nagata for providing unpublished data for us.

for industrial characteristics, they are firm-level variables and, we believe, reflect the technological and market environment of each firm accurately.

These variables are calculated as weighted averages in one more sense. As regards appropriability and innovation speed (to be explained presently), Goto and Nagata asked the companies to provide responses for each of product innovation and process innovation. Hence, we weighted these responses with the ratio of R&D spending on product innovation versus that on process innovations[11].

Three such firm-specific variables of industrial and technological characteristics will be now explained.

Appropriability

Goto and Nagata asked the respondents the percentage of their projects in the past three years for which each of the following eight means of protecting competitive advantages from innovations was effective – secrecy, patents, other legal protections, lead time, complementary sales and service, complementary manufacturing facilities and knowhow, complexity of production and product design, and others. They then reported the industrial averages of these percentages for each means.

Among these, we concentrate on the role of patents because, as discussed in Section 3, the effectiveness of patent protection is one of the major determinants of transaction costs and also because some of the other means listed above are not purely exogenous to the firms[12]. We define $APPRO_i$ as the extent of appropriability by patents. As shown in Table 2, the mean value of $APPRO_i$ equals 0.322, implying that, on average, the firms reported that patents were effective in about a third of the projects. As in the US (Levin et al., 1987; Cohen et al., 2000), it is highest among pharmaceutical firms:

[11] On the average of all manufacturing industries, 80.9 percent of the R&D cost was for product innovations and 14.7 percent for process innovations, with the rest being for miscellaneous category that was ignored in our analysis.

[12] One may alternatively use the maximum among the seven means (excluding 'others') as an appropriability variable. Such a variable may be appropriate as a determinant of R&D intensity because, whatever the means of appropriation, a higher appropriability is expected to stimulate R&D investment (Goto et al., 2002). However, in procured R&D, it is important that such appropriability is legally secured and patents are the most effective means for this purpose. Besides, in our preliminary regressions, we found that the maximum-based appropriability variable has a poorer explanatory power than the patent-based appropriability variable, presumably because some industries replied with unrealistically high numbers (e.g., 100 percent) for some of the non-patent means.

see Appendix Table 3 in which pharmaceuticals are included in chemicals.

As discussed earlier, according to the transaction cost theory, stronger property rights would enable the firms to engage in inter-firm relations with lower transaction costs; hence, $APPRO_i$ is expected to have a positive impact on procured R&D in the second hurdle. By preventing free-riding, they would also increase the private returns to R&D investment; hence, the incentive for R&D must be enhanced and $APPRO_t$ must have a positive coefficient in the first hurdle as well.

Our prediction of a positive effect of $APPRO_i$ in the second hurdle agrees with the theoretical prediction of Arora and Fosfuri (2003) on licensing. Empically, Gans et al. (2000) confirmed this prediction by showing that a stronger intellectual property protection increases the probability of cooperation between start-ups and incumbents. Hernán et al. (2003), on the other hand, argued that firms in sectors with stronger patent rights do not need to rely on research joint ventures to internalize spillovers and empirically confirmed this prediction. Similarly, Cassiman and Vergelers (2002) found a negative, though insignificant, effect of legal protection (including protection by patents) on the probability of R&D cooperation. If this argument is correct, then we should expect a negative coefficient of $APPRO_i$ on JRD_i. However, if joint R&D is formed to take advantages of the technological capabilities of the partners as the capability theory implies and not to internalize spillovers among the partners, then the transaction-cost reducing effect of $APPRO_i$ must be more prominent. With this view, we predict a positive coefficient.

Information flow

Goto and Nagata asked if each of twelve probable information sources was conducive to the 'proposal of a new project' or the 'completion of an existing project' in the past three years. They reported the percentage of firms who replied affirmatively for each source, each industry, and each of new project proposal versus project completion. Among the 12 sources, 'universities', 'public laboratories', and 'academic associations, etc.' will be hereafter called 'scientific sources', while 'suppliers with share ownership relationship', 'suppliers without share ownership relationship', 'customers', and 'competitors' will be called 'transaction-based sources'[13].

[13]The remaining five are 'joint ventures', 'consultants', 'other external sources', 'other R&D departments within the firm', and 'manufacturing department within the firm'. These were ignored because

We averaged among the three scientific sources and between new project proposal and project completion to get an industrial value of information flow from scientific sources, and then computed the firm-level value as an weighted average of industrial values in the manner discussed earlier. We call this variable 'scientific information flow' and denote it by $FLOWS_i$. We similarly calculated 'transaction-based information flow' from the average among the four transaction-based sources and denote it by $FLOWT_i$[14].

As shown in Table 2, $FLOWT_i$ is on average larger than $FLOWS_i$, suggesting that information is more frequent from transaction-based sources than from scientific sources although in a few industries, particularly pharmaceuticals, information flow from scientific sources overwhelms.

With a larger information flow, there must be a larger technological opportunity, which tends to stimulate in-house R&D as confirmed by Cohen and Levinthal, (1990) and Goto et al. (2002). This positive effect will take place not only because the larger information flow provides more opportunities for firms to innovate but also because firms need to enhance their absorptive capacity so as to take advantages of information flow (Cohen and Levinthal, 1989). We therefore expect $FLOWS_i$ and $FLOWT_i$ to have positive coefficients in the first hurdle.

Its impact on procured R&D can be more complex. On the one hand, a larger information flow implies that more 'seeds' are available outside of the firm, prompting the firm to invest in procured R&D to internalize these seeds. For instance, it may be easier to find partners with high technological competence and the firm may be tempted to take advantages of it through commissioned or joint R&D (Cassiman and Veugelers, 2002). On the other hand, such information flow may occur through knowledge spillovers, for instance, through published papers and human contacts, without the firm paying for it. Then the firm would have a lesser need for commissioned or joint R&D and licensing. Since these two types of information flow coexist in the Goto-Nagata survey, we cannot

joint venture is more likely a result than a cause of procured R&D, the impact of consultants and other external sources is difficult to predict, and intra-firm sources are unlikely to affect procurement of R&D from outside.

[14]One may alternatively define the two information flow variables based on the maximum among the relevant set of sources on the assumption that, if any one of the sources is very useful, the firm will attempt to take advantage of this source through R&D. However, similarly to the discussion in footnote 12 above, we found that these maximum-based variables are susceptible to a few extreme values (particularly in industries with small numbers of respondents); hence, we only report the results with mean-based variables.

a priori determine which of these two effects dominate. Consequently, the coefficients of $FLOWS_i$ and $FLOWT_i$ may be positive or negative in the second hurdle.

Speed of innovation

Goto and Nagata asked the firms to evaluate on a 5-point Likert scale how fast product innovation or process innovation took place in the past ten years in the industry. Based on the industrial average of this measure of 'innovation speed', we calculated $SPEED_i$ again as a weighted average.

When technological change is rapid, competition in terms of new products and/or new process is keen and the firm is under a strong pressure to innovate. Therefore, firms competing in such markets are more likely to undertake R&D, suggesting a positive coefficient in the first hurdle. Yet, even in high-tech industries, there are also firms who are not competing on the basis of technological strength but on the basis of low cost and/or non-R&D-based knowhow. These firms are often subcontractors or low-cost suppliers to large-scale assemblers and may have opted for non-R&D-based competition in fear of escalating R&D costs. That is, there may be a divide between R&D-intensive firms and non-R&D-based firms, and an accelerated speed of innovation may actually tilt this divide towards non-R&D-performing firms. If this is the case, we may have a negative coefficient for $SPEED_i$ in the first hurdle.

The effect on procured R&D can be also complex. Again, firms in an industry with fast innovation can be under a stronger pressure to come up with new products and/or new processes and, to fulfil this purpose, they may be more willing to utilize external resources. That is, they may be inclined to commission R&D or take part in joint R&D to speed innovation up, or to acquire new technology at once through licensing. Technological inter-firm partnerships have been in fact found in such high-tech industries as computers, semi-conductors, and biotechnology (Freeman, 1991; Hagedoorn, 2002; Powell et al., 1996).

However, there may not be a sufficient number of firms in such industries that are good enough to perform required commissioned R&D works. Although BSR does not give a precise definition of 'commissioned R&D', it states, in another part of the questionnaire, that 'commissioned production of products' is to have other firms manufacture or process finished products, semi-finished products, components, accessories, or materials by instructing them the specifications and standards. By analogy, respondents may have taken 'commissioned R&D' as including not only the commissioning of scientific discovery or development activities as described in Section 2 but also subcontracting of routine R&D-related works, say, data input, routine experiments and computation, and the maintenance of laboratory. Such subcontracting may be more prevalent in an industry with slower technological change as many of the works are standardized and many low-cost suppliers may provide such services. By contrast, in high-tech industries, commissioning of real and advanced R&D, as opposed to subcontracting, may be needed and yet only a small number of firms may have accumulated sufficient capabilities to perform such R&D. In consequence, the firm may have no choice but to perform it themselves.

In view of these possibilities, it is extremely difficult to predict the effect of $SPEED_i$ on procured R&D in the second hurdle of the model.

Table 3 summarizes our hypotheses on the signs of the coefficients in our double-hurdle model. It also includes $PRINT_i$ as an independent variable, which we will discuss later.

7 Empirical Results

7.1 The First Hurdle

We now present the results of our empirical analyses. Table 4 presents the estimated double-hurdle model when *ICRDD* and *CRD* (suppressing hereafter the subscript *i*) are taken as the dependent variables of the first hurdle and the second hurdle, respectively. Let us begin with the first pair of the estimated model, which is in the left half of the table.

In the first hurdle, all the variables except *FLOWT* and *SPEED* have significant coefficients (except *CFS*) with expected signs. *SPEED* has a significant and negative coefficient. This result suggests that an increased speed of innovation in the industry tends to discourage marginal R&D performers from making R&D investment rather than increase R&D incentives for them. In fact, among the two-digit SIC industries, electrical machinery has the highest *SPEED* (see Appendix Table 3) but only about a half of the firms show positive in-house R&D (see Appendix Table 1) whereas, in the chemical industry, about 80 percent of the firms show positive in-house R&D but its

SPEED is lower than the entire average. However, if we look only at the firms with any R&D activity (i.e., *RDD* = 1), then the in-house R&D intensity (*RDINT*) of the electrical machinery industry is 2.4 percent, which is fourth highest among the industries and 0.7 percent point higher than the entire mean (see Appendix Table 2). That is, in this industry, R&D-intensive large firms coexist with a large number of non-R&D-performing small firms. The presence of such an industry explains why *SPEED* has a negative coefficient in the first hurdle. This result is consistent with the positive coefficient of *SPEED* on R&D intensity that is obtained in an OLS regression with R&D-performing firms only[15].

Another unexpected result is the significant and negative coefficient of *FLOWT*, as it implies that a firm in an industry where information flow from transaction-based sources is more useful is *less* likely to expend for R&D. Looking at the industrial means (see Appendix Table 3), one finds that *FLOWT* is highest in printing (including publishing). In this industry, customers are the most important information source among the four transaction-based sources. Presumably, most products are custom-made and hence close and frequent relationship with customers is required, through which the customers provide information leading to the start of new projects or the completion of existing projects, explaining the high value of *FLOWT*. This industry, however, is one of the least R&D-intensive: in fact, the proportion of firms performing in-house R&D is only 13 percent, the lowest among the industries (see Appendix Table 1), suggesting that R&D projects are carried out only by a small number of large R&D-oriented firms and/or projects need not involve R&D expenditures.

In view of this peculiar behavior of the printing industry, we added a dummy variable, *PRINT*, which is one if and only if the firm's main business is in printing, publishing, and allied industries. The estimation result with this dummy variable is shown in the right half of Table 4. As expected, *PRINT* has a very significant negative effect in the first hurdle. In addition, the coefficient of *FLOWT* turns to positive, if insignificant. This result clearly suggests that the negative coefficient of *FLOWT* in the first regression result owes to the peculiar nature of the printing industry. In other industries, there is no tendency that the propensity to perform R&D is negatively related to the level of transaction-based information flow.

[15]The result of this OLS regression is suppressed to save space but is available in Nakamura and Odagiri (2003).

7.2 The Second Hurdle

Now let us go to the estimation results of the second hurdle in Table 4. Basically, all the sign conditions shown in Table 3 are satisfied. The estimated positive coefficient of *VI* is consistent with the hypothesis that a diversified firm possesses a vertically broader capability, which makes procured R&D easier and more useful, but is inconsistent with the hypothesis that a more integrated firm is operating under an environment with higher market transaction costs. The coefficient of *CFS* is insignificant, supporting neither the hypothesis of cost-sharing and risk-sharing motivation for commissioned R&D nor the hypothesis that investment in commissioned R&D is riskier than investment in physical assets and therefore needs to be financed internally.

APPRO has an expected positive coefficient, supporting the hypothesis that a stronger patent right helps the firms to reduce transaction costs. *FLOWS* has a significantly positive coefficient, suggesting that information flow from scientific sources enriches technological opportunity and the firms are motivated to commission R&D to take advantages of such opportunity. As in the first hurdle, *FLOWT* has a negative and significant coefficient but, when *PRINT* is added, the significance is lost. The coefficient of *PRINT* is negative and significant, suggesting that printing and publishing firms are inactive in commissioned R&D as well.

SPEED has negative coefficients as in the first hurdle. In an industry with fast innovation, the firm may feel a stronger need to accumulate capabilities internally and/or there may not be many qualified parties (firms, laboratories, or universities) to commission R&D to.

7.3 Determinants of the Three Modes of Procured R&D

So far we have only considered commissioned R&D as a means of procured R&D. We will now expand the analysis and estimate the double-hurdle model with each mode of procured R&D as an alternative second-hurdle variable. The results are summarized in Table 5, which shows only the estimated results of the second hurdle because we confirmed that the estimation result of the first hurdle is insensitive to the choice of the dependent variable in the second hurdle. In addition, even though we now used *RDD* as the first-hurdle variable in place of *ICRDD* for the reason discussed in Section 5, the estimated first-hurdle results are basically unchanged. In other words, the estimation results of the first-hurdle equation shown in Table 4 stand regardless of whether *RDD* or *ICRDD* is taken in the first hurdle and which of the procured R&D variable is taken in the second hurdle[16].

In view of the peculiarity of the printing industry as shown above, we only present results with *PRINT*.

The estimated *CRD* equation is slightly different from that in Table 4 (in the far right column) because the first-hurdle variable is now *RDD*; however, the signs of all the coefficients are unchanged. These signs are the same in the *CRDN* equation, that is, when in-group commissioned R&D is excluded. The only difference from the *CRD* equation is that the negative coefficient of *PC* is now significant as hypothesized in Section 6.

The same signs generally hold in the *JRD* and *TA* equations, suggesting the similarly of the determinants of the three modes of procured R&D. However, a few interesting variations appear regarding the coefficients of industrial variables. First, *FLOWS* has positive and significant coefficients in the *CRD* and *JRD* equations but the significance is lost in the *TA* equation. In an industry with abundant information flow from scientific sources, commissioned R&D and joint R&D tend to be more active but there is no significant difference regarding technology acquisitions. It is suggested that, in such an industry, firms are eager to incorporate advanced scientific knowledge through commissioning of R&D and joint R&D.

Second, the coefficient of *FLOWT*, which is insignificant but negative in the *CRD* equation, is positive and significant in the *JRD* and *TA* equations. That is, in an industry with frequent information flow from transaction-based sources, such as suppliers, customers, and competitors, joint R&D is more actively performed as well as licensing, but not commissioned R&D. It is suggested that, in an industry in which such information flow is useful, the firm finds more opportunity for joint R&D with its transaction partners or for licensing-in of technology from them. By contrast, commissioning of R&D is more likely to occur to scientific sources, such as universities, as just discussed or, possibly, to R&D specialists.

Third, *SPEED* has a significant negative coefficient in the *CRD* equation, negative but an insignificant one in the *JRD* equation, and a positive and significant one in the *TA* equation. Presumably, when innovation occurs rapidly, the firm is keen to catch up with

[16]For detailed estimation results, see Nakamura and Odagiri (2003).

innovation through licensing-in of already invented technologies, rather than through commissioning of R&D because it would take substantial time until the outcome is gained from commissioned R&D and the predictability of its outcome is low.

In contrast to these three variables, the remaining industrial variable, *APPRO*, has consistently positive and significant coefficients regardless of the modes of procured R&D, strongly supporting the hypothesis that effective protection by patents contributes to the reduction of transaction costs.

Many of these results do not hold in the *CRDI* equation. In particular, the coefficient of *PC* is positive and strongly significant as expected, making a good contrast to the negative and significant coefficient in the *CRDN* equation. Parent-controlled firms tend not to commission R&D to outside of the group but they do commission more R&D within the group. Presumably, the decision on the commissioning of R&D to outside is made by parent firms. In-group R&D capabilities are probably also concentrated to parent firms or in-group R&D companies, and the subsidiaries commission necessary R&D to these firms.

Furthermore, all the coefficients of industry variables are insignificant in the *CRDI* equation and so are the coefficients of *VI* and *DIV*, the variables showing the vertical and diversifying breadth of the firm's capabilities. We may therefore conclude that the activity of in-group commissioning of R&D is dependent on neither the industrial characteristics nor the firm's organizational form.

7.4 Estimation Results for Large Firms

In order to investigate if our use of the double-hurdle model does matter, we show, in the left half of Table 6, the determinants of procured R&D estimated as single-equation Tobit models. Comparing it with Table 5, we find that the general tendency is the same, confirming the robustness of our estimation results. Yet, z values tend to be higher in the double-hurdle model estimations (except *RDINT*) and some of the statistical significance is lost in the Tobit results (e.g., *APPRO* in the *JRD* equation and *SPEED* in the *TA* equation). This difference comes from the fact that, in the double-hurdle model, the second-hurdle equation is relevant only for R&D-performing firms (see the likelihood function in Appendix 2) whereas, in the Tobit model, all the sample firms, whether they are performing R&D or not, are treated equally. Because *RDINT* is a decisive variable to separate R&D-performing firms from others (as *RDINT* = 0 for all non-R&D-performing firms), it is estimated to have a larger-than-real explanatory power in the Tobit model. The other variables, by contrast, lose their explanatory power because of the presence of so many zero-valued dependent variables.

This difficulty with the Tobit model is mitigated when we restrict our sample to large firms, because non-R&D-performing firms become relatively unimportant among these large firms.

The Small and Medium Enterprise Basic Law of Japan defines 'small and medium enterprises' (SME) as the firms with capitalization not in excess of 300 million yen or with 300 or fewer employees. Hence, in the following, we define 'large firms' as those that do not satisfy this criterion of SME. There were 2,026 such firms in our sample, which comprise 14.4 percent of the whole sample. Among these, 1,715 (84.6 percent of 2,026) performed at least one form of R&D, whether in-house or procured, that is, *RDD* = 1. Hence, non-R&D-performing firms are minority among the large firms, in contrast to the fact that non-R&D-performing firms accounted for 52.8 percent among the entire sample.

The right-hand half of Table 6 shows the Tobit estimation results for these large firms. Comparing it with the estimation results of the entire sample in the left-hand half of the same table or with the second-hurdle estimation results in Table 4, we find that the results are reasonably similar, with only a few changes. First, the coefficients of *PC* are not significant among large firms, suggesting that large subsidiary firms are acting more like independent firms in terms of their R&D activity. This result should appear reasonable if one recalls the fact that such large Japanese firms as JVC and Hino Motors (without implying that these firms are in fact in our sample) are subsidiaries (of Matsushita Electric and Toyota, respectively).

Second, the results on industrial variables are mixed. Compared to the results with the entire sample, in the *CRD* equation, *FLOWS* and *SPEED* lose significance. When information flow from scientific sources is abundant, large firms may be able to acquire and absorb such information through papers and other spillovers without commissioning R&D. A larger incentive to speed up innovation through commissioning R&D may be stronger among large firms, offsetting the desire to accumulate capabilities through in-house R&D. In the *TA* equation, the positive coefficient of *SPEED* is strengthened in terms of both the coefficient and its statistical fit. In the *JRD* and *TA* equations, *APPRO* becomes insignificant. This result is unsatisfactory, particularly because *APPRO* is constructed from the survey of large firms only and should therefore reflect the views of large firms better. The estimation results of the double-hurdle model appear more reasonable in this regard.

In conclusion, even though most of the general results hold even with single-equation Tobit models, we believe that double-hurdle models provide more reasonable estimates, particularly when the behavior of mostly non-R&D-performing small and medium enterprises should be also accounted.

8 Summary and Conclusions

In this paper, we argued for the importance of the issue of R&D boundaries of the firm, namely, the firm's choice between performing R&D in-house *versus* procuring it from outside. Various modes of R&D procurement are available and we classified them between commissioned R&D, joint R&D, and technology acquisitions (i.e., licensing-in). There is an important difference among these in terms of the timing of contract and the extent of definability and uncertainty at the time of contract.

Making use of a large-scale database of manufacturing firms in Japan, we have empirically analyzed the determinants of these three modes of procured R&D to test the hypotheses built around the two major theories – the transaction cost theory and the capability theory. In view of the presence of a large number of firms who failed to perform any R&D activity at all, we formulated the R&D decision process as a double-hurdle model and estimated this model with a maximum likelihood methodology.

Generally, the estimation results support the two theories. Most importantly, we found positive impacts of firm size, in-house R&D intensity, diversification, and vertical integration, which supports the hypothesis that the presence of a large and broad absorptive capacity is a contributing factor for procured R&D by making it easier for the firms to seek potential partners, evaluate them, monitor R&D alliances, and utilize the outcome for commercialization. We have also found a positive effect of the index of appropriability by patents, which supports the hypothesis that appropriability reduces transaction costs. Many of these results apply to R&D commissioned to non-group organizations, joint R&D, and licensing but not necessarily to R&D commissioned to in-group firms, suggesting that groups are quasi-internal organizations and therefore monitoring and appropriability issues do not arise.

We also found that (1) information flow from scientific sources (universities, public laboratories, and academic associations) stimulates commissioned R&D and joint R&D, (2) information flow from transaction-based sources (suppliers, customers, and competitors) stimulates joint R&D and technology acquisitions and, (3) firms in fast-innovating industries tend to rely on licensing-in to acquire completed technologies and rather refrain from commissioning R&D, presumably because it would take time before the outcome is to be gained from commissioned R&D.

Of course, there still remain many issues to be addressed. The first is the adequacy of the measure of R&D procurement activity. For instance, the number of partners in a joint R&D project need not be related to the intensity and efficiency of the project, particularly because firms may be more tempted to free ride on the partners' efforts if there are many participants. Technology acquisitions are measured by the amount the firm paid for acquired technologies. However, since most payment for licensing is composed of fixed initial payment and running royalty which is usually a fixed percentage of sales, it can violently fluctuate from year to year and the firm keeps paying for many years after the actual technology acquisition has taken place.

Second, there remains a possibility of endogeneity of some of the independent variables. In reality, the firm would first determine how much resources to be invested for its entire R&D activity and, then, would determine the best mix of in-house R&D, commissioned R&D, joint R&D, and licensing. With the adoption of a double-hurdle model, we believe we have made an important step towards analyzing this sequence of decisions. Still, we have not yet fully investigated the simultaneous decision of in-house R&D and the three modes of procured R&D and instead estimated the determinants of each means of procured R&D separately, using in-house R&D intensity as an explanatory variable. How to model such simultaneous decision of the firm and how to estimate such a model are big questions that we intend to pursue in the future. The present analysis, we hope, provides a good starting point towards such a more comprehensive analysis.

Appendix 1. Data Source

The *Basic Survey of Business Structure and Activities* (BSA) was first compiled by the then Ministry of International Trade and Industry (MITI; reorganized as the Ministry of Economy, Trade and Industry or METI in 2001) in 1992 and then every year since 1995. BSA covers all the firms in Japan that meet the following three conditions; (1) the firm has an establishment classified to either major division D (mining), F (manufacturing) or I (wholesale and retail trade, eating and drinking place) of the Japanese Standard Industrial Classification (JSIC), (2) with 50 employees or more, and (3) with capitalization (i.e., the book value of equity) of 30 million yen or more. With METI's kind permission, we use the unpublished firm-level data of this survey for 1997.

Aggregated industry data of BSA has been published in a series of official reports[17]. However, our scheme of industrial classification is different from that used in these reports. They classified each firm into one of the 2-digit JSIC industries according to the 3-digit industry with largest sales. We aggregated the firm's 3-digit sales composition to that of 2-digit and, then, classified the firm into the industry with the largest sales. For instance, suppose that the firm sells products in three 3-digit industries, say, 303 (communication equipment), 304 (computers), and 329 (miscellaneous precision instrument), which comprise, respectively, 30, 30, and 40 percent of the firm's total sales. Then, the official report classifies the firm into the 2-digit industry 32 (precision instrument) whereas we classified it into the 2-digit industry 30 (electrical equipment) because the sum of the sales in industries 303 and 304 outweighs that in industry 329. Industry statistics shown in Appendix Tables 1, 2, and 3 were calculated according to this classification scheme of ours.

The sample in our analysis consists of all the manufacturing firms in the survey[18]. However, apparent 'outliers' were eliminated. For instance, one firm reported that it had joint R&D agreements with 315 partners, which is extraordinary large compared to other firms. It is, in fact, difficult to imagine that the firm can maintain effective R&D collaboration with such many partners. We eliminated 21 similarly apparent outliers so that all the samples satisfy the following conditions (see Tables 1 and 2 for the variable

[17] See http://www.meti.go.jp/english/statistics/data/h2c1tope.html for a preliminary report in English.

[18] Similarly to our 2-digit industrial classification explained in the previous paragraph, we aggregated the firm's 3-digit sales composition to that of 1-digit and defined manufacturing firms as the firms whose largest 1-digit industry classification is F (manufacturing).

symbols): (1) $CRD < 40,000$, (2) $JRD < 150$, (3) $TA < 14,000$, (4) $RDINT < 0.35$, (5) $VI < 1$, (6) $-1 < CFS < 1$. The final sample contains 14,070 firms.

The industrial distribution of these firms is shown in the second column of Appendix Table 1, together with the number of firms that reported a positive value for each dependent variable. Appendix Table 2 shows industrial means of in-house and procured R&D intensities, calculated as the ratios (in percentage) to the firm's sales. Note that *JRD* is the number of partners in joint R&D; hence, its ratio to sales is difficult to interpret and not comparable to the R&D intensity as usually defined, such as the ratio of *IRD* to sales. Appendix Table 3 gives the industrial means of the explanatory variables.

Appendix 2. The Double-Hurdle Model

Following Flood and Grasjo (2001), we write a two-equation model as follows:

$$d_i^* = x_{1i}'\beta_1 + v_i \tag{1}$$

$$y_i^* = x_{2i}'\beta_2 + \epsilon_i \tag{2}$$

where, in our study, d_i^* is a latent variable representing participation in R&D and y_i^* is a latent variable representing, for instance, commissioned R&D. x_{1i} and x_{2i} are observable vectors of explanatory variables, β_1 and β_2 are the vectors of parameters, and the random errors $(v_i, \epsilon_i)'$ are assumed to obey i.i.d. bivariate normal distribution (BVN) with mean zero and variance-covariance matrix as follows[19]:

$$(v_i, \epsilon_i)' \sim BVN(0, \Sigma), \ \ \Sigma = \begin{bmatrix} 1 & \sigma\rho \\ \sigma\rho & \sigma^2 \end{bmatrix} \tag{3}$$

We impose the following threshold conditions:

$$d_i = \begin{cases} 1 \ \ if \ \ d_i^* > 0 \\ 0 \ \ if \ \ d_i^* \leq 0 \end{cases} \tag{4}$$

$$y_i = \begin{cases} y_i^* \ \ if \ \ d_i = 1 \ \ and \ \ y_i^* > 0 \\ 0 \ \ otherwise \end{cases} \tag{5}$$

where d_i is an observed value, which equals $ICRDD_i$ in our study. Similarly, y_i in our study is CRD_i, etc. Using these equations, we write the likelihood function as follows:

$$\begin{aligned} L = \prod_{d_i=0}(1 - F(v_i > -x_{1i}'\beta_1)) \prod_{d_i=1,y_i=0} F(v_i > -x_{1i}'\beta_1, -x_{2i}'\beta_2 \geq \epsilon_i) \\ \times \prod_{d_i=1,y_i>0} F(v_i > -x_{1i}'\beta_1, \epsilon_i > -x_{2i}'\beta_2) f(\epsilon_i | v_i > -x_{1i}'\beta_1, \epsilon_i > -x_{2i}'\beta_2) \end{aligned} \tag{6}$$

where $f(\cdot)$ and $F(\cdot)$ denote density and cumulative distribution functions respectively. The first multiplicative term corresponds to the probability of the case in which $d_i = 0$

[19]In Cragg's original model, the error terms, v_i and ϵ_i, were assumed independent. However, as equations (1) and (2) are both related to the R&D activity of the same firm, it is likely that unobservable common factors generate correlation between the residual errors. We thus assume equation (3). While this assumption follows that of the 'double-hurdle dependent model' of Jones (1992), our model differs from his in an important way. In Jones's model, the information on d_i is lacking and it was assumed that $d_i = 1$ if and only if $y_i > 0$. We, on the other hand, have information on d_i (namely, $ICRDD_i$) and utilize this information to formulate the likelihood function below.

(and hence $y_i = 0$), and the second term, $d_i = 1$ and yet $y_i = 0$. The last term gives the probability that, given that these double hurdles are cleared, y_i^* is realized as y_i.

Combining all these equations, we have

$$L = \prod_{d_i=0} \Phi(-x'_{1i}\beta_1) \prod_{d_i=1,y_i=0} \Phi_2(x'_{1i}\beta_1, -x'_{2i}\beta_2/\sigma, \rho)$$
$$\times \prod_{d_i,y_i>0} \left\{ \Phi\left(\frac{x'_{1i}\beta_1 + \frac{\rho}{\sigma}(y_i - x'_{2i}\beta_2)}{\sqrt{1-\rho^2}} \right) \frac{1}{\rho} \phi((y_i - x'_{2i}\beta_2)/\rho) \right\} \quad (7)$$

where Φ and Φ_2 are the standard normal distribution functions for, respectively, uni-variate and bi-variate cases. By maximizing (7), we get consistent estimates of β_1, β_2, and Σ.

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Table 1. R&D Variables: Descriptive Statistics

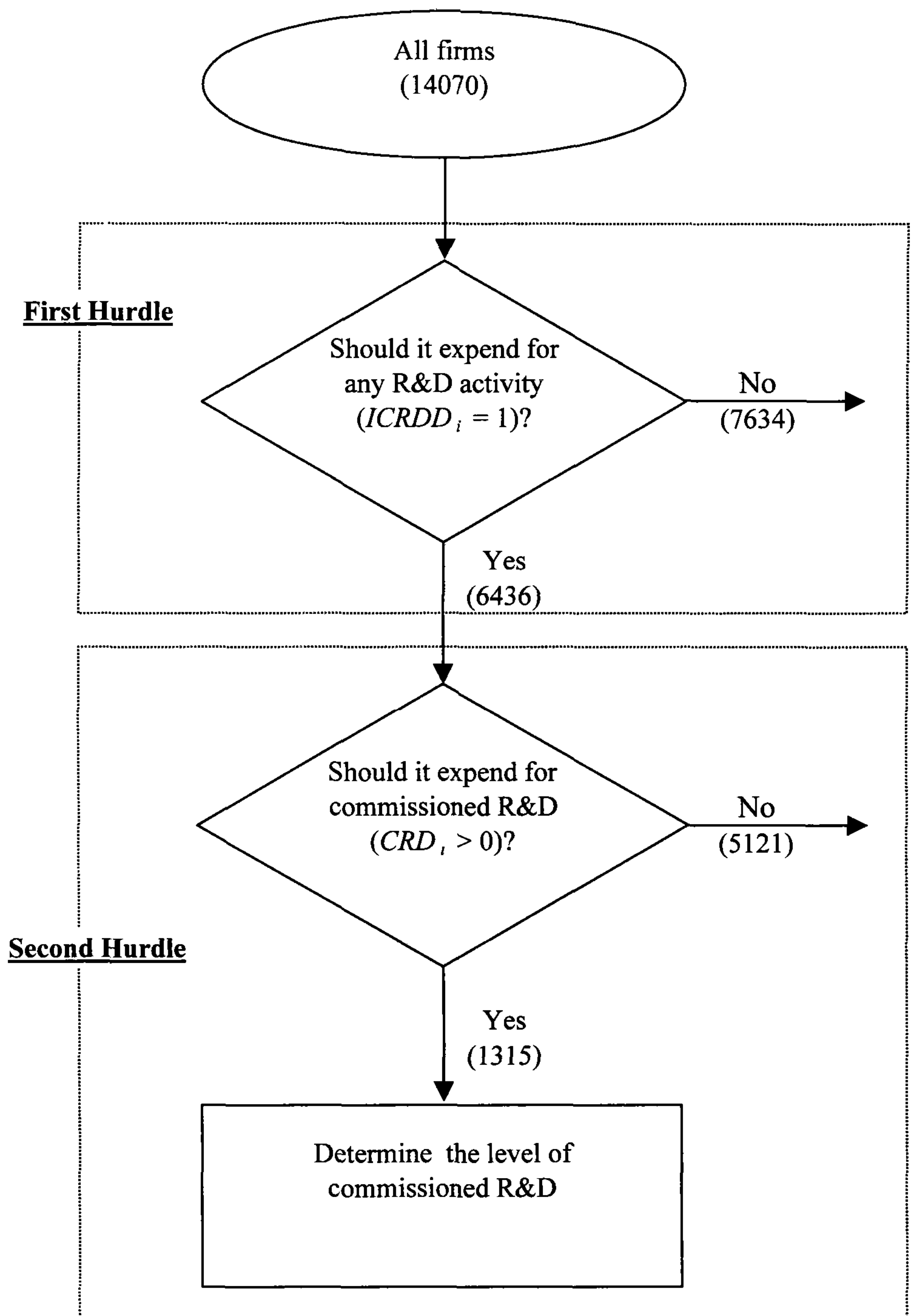
(in million yen, except *n* and *JRD*)

Symbol	Description	Whole sample				Sample with positive values			
		n	Mean	Std. Dev.	Max	*n*	Mean	Median	Std. Dev.
IRD	In-house R&D expenditures	14070	466.46	6632.40	427800	6281	1044.91	54.00	9896.60
CRD	Total commissioned R&D expenditures	14070	21.20	294.42	14907	1315	226.79	15.00	938.87
CRDN	Non-group commissioned R&D expenditures	14070	16.85	271.93	14907	1150	206.15	10.69	930.81
CRDI	In-group commissioned R&D expenditures	14070	4.35	80.07	4336	296	312.85	29.91	910.61
JRD	Number of joint R&D partners	14070	0.23	1.98	75	950	3.47	2.00	6.83
TA	Payment for technology acquisitions	14070	11.37	178.53	8215	834	191.76	16.00	709.72

Notes: 1. n = number of observations (i.e., number of firms).
2. For any variable, the median for the 'whole sample' equals 0 and the maximum value for the 'sample with positive values' equals that for the 'whole sample'.
3. Subscript i is suppressed.

Data Source: BSA

Figure 1. R&D Decision Flow Chart: The Double-Hurdle Model



Notes: 1. $ICRDD_i = 1$ if $IRD_i+CRD_i > 0$
$= 0$ if $IRD_i+CRD_i = 0$.
2. In parentheses are the number of firms.

Table 2. List of Independent Variables and Descriptive Statistics

Symbol (subscript *i* suppressed)	Name	Description	Whole sample (n=14070) Mean	Median	Std. Dev.	Min	Max	Sample with *RDD*=1 (n = 6648) Mean	Median	Std. Dev.
RDINT	In-house R&D intensity	In-house R&D expenditure / sales	0.008	0	0.018	0	0.332	0.017	0.009	0.024
LSALE	Size	Sales in natural logarithm	8.407	8.191	1.287	4.454	15.866	8.907	8.675	1.375
VI	Vertical integration	Value-added / sales	0.293	0.277	0.131	0.001	0.986	0.283	0.272	0.112
DIV	Diversification	Index of product diversification ($1\text{-}H^{1/2}$, where H = Herfindahl index)	0.143	0.092	0.151	0	0.656	0.167	0.133	0.156
CFS	Cash flow ratio	Cash flow / sales	0.044	0.039	0.059	-0.931	0.964	0.047	0.042	0.058
PC	Parent-controlled	A dummy variable that equals 1 if and only if the firm has a parent company	0.280	0	0.449	0	1	0.262	0	0.440
APPRO	Appropriability	Appropriability by patents*	0.322	0.314	0.070	0.142	0.615	0.332	0.331	0.075
FLOWS	Scientific information flow	The average of information flow from three scientific sources (universities, public laboratories, and academic associations)*	0.385	0.369	0.081	0.247	0.825	0.394	0.369	0.101
FLOWT	Transaction-based information flow	The average of information flow from four transaction-based sources (suppliers with or without share ownership relationship, customers, and competitors)*	0.463	0.472	0.080	0.341	0.625	0.458	0.462	0.074
SPEED	Innovation speed	Speed of innovation change*	3.064	3.090	0.281	2.038	3.786	3.064	3.063	0.281
PRINT	Printing and allied industry dummy	A dummy variable that equales 1 if and only if the firm is in printing, publishing, and allied industries	0.056	0	0.230	0	1	0.017	0	0.130

Note: n = number of observations (i.e., number of firms). $RDDi=1$ if and only if min ($IRDi$, $CRDi$, $JRDi$, TAi)>0.
Data Source: BSA, except * by Goto and Nagata (1996)

Table 3. Hypothesized Signs of the Coefficients

	Dependent Variables	
	First Hurdle	Second Hurdle
Independent Variables	*RDD* or *ICRDD*	*CRD* (or *CRDN*, *CRDI*), *JRD*, or *TA*
RDINT		+
LSALE	+	+
VI	+	+/−
DIV	+	+
CFS	+	+/− (likely - for *TA*)
PC	−	− (likely + for *CRDI*)
APPRO	+	+
FLOWS	+	+/−
FLOWT	+	+/−
SPEED	+/−	+/−
PRINT	−	−

Note: Subscript i is suppressed.

Table 4. Estimation Results of the Double Hurdle Model

Dependent var.	First hurdle ICRDD	Second hurdle CRD	First hurdle ICRDD	Second hurdle CRD
RDINT		5,194.386		5,167.408
		(5.97)***		(5.91)***
LSALE	0.476	340.369	0.484	341.480
	(38.50)***	(7.30)***	(38.75)***	(7.30)***
VI	1.174	625.825	1.271	656.230
	(10.94)***	(3.31)***	(11.70)***	(3.44)***
DIV	0.793	314.247	0.707	278.098
	(10.40)***	(2.93)***	(9.20)***	(2.61)***
CFS	0.102	30.981	-0.033	-5.982
	(0.45)	(0.08)	(-0.14)	(-0.02)
PC	-0.200	-6.386	-0.221	-13.353
	(-7.87)***	(-0.20)	(-8.66)***	(-0.42)
APPRO	2.292	2,124.185	1.518	1,898.605
	(12.56)***	(5.82)***	(8.09)***	(5.50)***
FLOWS	1.015	715.663	1.308	827.528
	(6.24)***	(3.46)***	(8.16)***	(3.86)***
FLOWT	-0.957	-525.078	0.201	-134.098
	(-6.70)***	(-2.52)**	(1.24)	(-0.64)
SPEED	-0.170	-139.879	-0.122	-123.609
	(-3.96)***	(-2.48)**	(-2.83)***	(-2.22)**
PRINT			-1.040	-492.434
			(-14.67)***	(-3.54)***
Constant	-4.683	-4,971.448	-5.253	-5,163.867
	(-25.45)***	(-7.16)***	(-27.94)***	(-7.17)***
SIGMA	938.492		938.291	
	(7.21)***		(7.20)***	
RHO	0.953		0.955	
	(66.29)***		(55.57)***	
Log likelihood	-20474.98		-20347.38	

Notes: 1. No. of observations = 14070.
2. Robust z statistics in parentheses.
3. * significant at 10%; ** at 5%; *** at 1%.

Table 5. The Determinants of Procured R&D: The Second-Hurdle Estimation Results

Mode of Procured R&D	*CRD*	*CRDN*	*CRDI*	*JRD*	*TA*
RDINT	5,535.647	5,518.671	3,238.026	25.166	2,316.237
	(6.04)***	(5.55)***	(3.72)***	(3.44)***	(4.03)***
LSALE	338.874	316.566	188.746	2.164	325.721
	(7.30)***	(6.56)***	(5.72)***	(8.45)***	(7.01)***
VI	643.295	505.411	150.253	5.907	830.595
	(3.41)***	(2.76)***	(0.63)	(3.17)***	(4.25)***
DIV	278.249	336.786	103.825	7.398	254.792
	(2.62)***	(3.04)***	(0.87)	(6.08)***	(2.48)**
CFS	-15.035	169.404	-30.193	-2.932	-429.075
	(-0.04)	(0.54)	(-0.06)	(-0.98)	(-1.20)
PC	-12.785	-114.789	229.138	-0.654	3.585
	(-0.40)	(-2.91)***	(5.09)***	(-1.84)*	(0.11)
APPRO	1,875.869	2,036.336	213.622	6.746	1,122.837
	(5.47)***	(5.48)***	(0.70)	(2.68)***	(4.18)***
FLOWS	824.089	904.348	-158.163	9.519	271.224
	(3.85)***	(3.88)***	(-0.67)	(5.10)***	(1.57)
FLOWT	-133.020	-203.695	186.441	9.438	347.438
	(-0.63)	(-0.95)	(0.75)	(3.96)***	(1.66)*
SPEED	-125.439	-147.891	-24.047	-0.724	101.083
	(-2.26)**	(-2.51)**	(-0.37)	(-1.22)	(1.68)*
PRINT	-491.648	-488.668	-259.343	-7.243	-461.003
	(-3.54)***	(-3.16)***	(-1.86)*	(-5.40)***	(-3.33)***
Constant	-5,126.654	-4,922.450	-3,326.851	-44.426	-5,387.194
	(-7.17)***	(-6.45)***	(-5.89)***	(-9.49)***	(-6.96)***
SIGMA	937.280	922.209	694.359	9.653	744.535
	(7.20)***	(6.48)***	(7.22)***	(12.13)***	(7.19)***
RHO	0.945	0.958	0.893	0.977	0.946
	(60.29)***	(37.75)***	(33.57)***	(35.03)***	(58.98)***
Log likelihood	-20379.05	-18930.08	-11245.52	-13125.74	-15979.52

See Note to Table 4.

Table 6. Determinants of Procured R&D in All Firms vs. Large Firms: Tobit Estimation Results

	All firms					Large firms				
	CRD	*CRDN*	*CRDI*	*JRD*	*TA*	*CRD*	*CRDN*	*CRDI*	*JRD*	*TA*
RDINT	11,685.849	11,120.790	6,421.634	86.856	5,981.097	14,432.390	11,502.228	10,350.146	82.638	7,756.675
	(6.99)***	(6.30)***	(5.35)***	(8.31)***	(6.67)***	(6.02)***	(5.04)***	(4.84)***	(4.50)***	(5.77)***
LSALE	288.714	271.490	159.560	1.747	294.525	524.083	510.865	202.525	2.587	383.065
	(7.21)***	(6.48)***	(5.49)***	(7.54)***	(6.89)***	(6.44)***	(5.94)***	(3.56)***	(4.18)***	(6.20)***
VI	448.304	340.099	67.637	2.989	669.808	1,264.879	1,359.488	-181.010	6.450	511.918
	(2.86)***	(2.19)**	(0.34)	(1.90)*	(4.10)***	(2.36)**	(2.60)***	(-0.32)	(1.22)	(1.26)
DIV	260.406	310.778	113.985	7.010	268.207	461.769	535.954	358.062	11.430	572.740
	(2.50)**	(2.87)***	(0.98)	(5.89)***	(2.60)***	(1.68)*	(1.88)*	(1.35)	(3.68)***	(2.62)***
CFS	-50.276	105.780	-62.109	-2.892	-403.908	-822.224	-242.578	-1,023.508	-2.231	-961.008
	(-0.14)	(0.32)	(-0.12)	(-0.94)	(-1.15)	(-0.85)	(-0.28)	(-1.00)	(-0.32)	(-1.33)
PC	-3.200	-105.933	233.253	-0.604	5.629	143.547	-5.216	353.024	0.318	93.184
	(-0.10)	(-2.71)***	(5.16)***	(-1.70)*	(0.17)	(1.63)	(-0.06)	(3.47)***	(0.34)	(1.18)
APPRO	1,492.612	1,672.470	50.103	3.614	861.509	2,702.370	3,402.256	353.302	7.926	603.164
	(4.89)***	(5.09)***	(0.17)	(1.46)	(3.42)***	(3.64)***	(4.37)***	(0.46)	(1.08)	(1.15)
FLOWS	559.864	675.827	-401.943	6.881	104.623	635.035	912.865	-1,598.804	8.792	491.411
	(2.73)***	(3.09)***	(-1.57)	(3.65)***	(0.58)	(1.17)	(1.68)*	(-2.37)**	(1.72)*	(1.29)
FLOWT	-107.736	-159.893	131.507	9.449	399.853	-259.445	-77.902	-432.060	11.736	1,175.550
	(-0.51)	(-0.74)	(0.53)	(3.92)***	(1.88)*	(-0.44)	(-0.13)	(-0.66)	(1.71)*	(2.38)**
SPEED	-144.672	-163.827	-42.843	-0.833	81.588	-212.037	-281.625	-81.557	-2.778	372.744
	(-2.64)***	(-2.80)***	(-0.68)	(-1.42)	(1.38)	(-1.53)	(-1.91)*	(-0.54)	(-1.77)*	(2.70)***
PRINT	-442.983	-449.797	-218.378	-6.501	-459.106	-858.567	-1,079.357	-114.036	-6.803	-966.434
	(-3.28)***	(-2.99)***	(-1.59)	(-4.92)***	(-3.31)***	(-2.05)**	(-2.25)**	(-0.26)	(-1.74)*	(-2.79)***
Constant	-4,388.492	-4,269.847	-2,824.888	-38.027	-4,912.897	-7,869.947	-8,037.920	-3,117.333	-50.708	-7,489.769
	(-7.05)***	(-6.35)***	(-5.65)***	(-8.88)***	(-6.85)***	(-6.25)***	(-5.82)***	(-3.43)***	(-4.59)***	(-6.25)***
Observations	14070	14070	14070	14070	14070	2026	2026	2026	2026	2026
Log likelihood	-12720.49	-11178.98	-3171.37	-5419.72	-8057.65	-5098.42	-4507.08	-1403.96	-1736.56	-4254.83

Note: *t* statistics in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix Table 1. Industrial Distribution of Firms

	No. of all sample firms	No. of firms with positive in-house or procured R&D											
Industry		*IRD*		*CRD*		*CRDN*		*CRDA*		*JRD*		*TA*	
Food	1285	535	(41.6)	53	(9.9)	45	(8.4)	10	(1.9)	36	(6.7)	13	(2.4)
Beverages, tobacco and feed	281	148	(52.7)	25	(16.9)	23	(15.5)	5	(3.4)	10	(6.8)	6	(4.1)
Textile mill products	372	143	(38.4)	28	(19.6)	21	(14.7)	10	(7.0)	17	(11.9)	6	(4.2)
Apparel and other finished products	520	92	(17.7)	20	(21.7)	19	(20.7)	1	(1.1)	9	(9.8)	3	(3.3)
Lumber and wood products	151	28	(18.5)	3	(10.7)	3	(10.7)	0	(0.0)	7	(25.0)	1	(3.6)
Furniture and fixtures	176	78	(44.3)	10	(12.8)	10	(12.8)	1	(1.3)	5	(6.4)	3	(3.8)
Pulp, paper and paper products	379	78	(20.6)	6	(7.7)	4	(5.1)	2	(2.6)	12	(15.4)	7	(9.0)
Printing and allied industries	786	103	(13.1)	12	(11.7)	9	(8.7)	4	(3.9)	11	(10.7)	7	(6.8)
Chemical and allied products	868	699	(80.5)	264	(37.8)	243	(34.8)	47	(6.7)	129	(18.5)	115	(16.5)
Petroleum and coal products	60	35	(58.3)	13	(37.1)	13	(37.1)	3	(8.6)	7	(20.0)	6	(17.1)
Plastic products	651	278	(42.7)	53	(19.1)	47	(16.9)	12	(4.3)	49	(17.6)	36	(12.9)
Rubber products	157	93	(59.2)	15	(16.1)	11	(11.8)	4	(4.3)	15	(16.1)	9	(9.7)
Leather tanning, leather products and fur skins	47	22	(46.8)	8	(36.4)	8	(36.4)	0	(0.0)	2	(9.1)	0	(0.0)
Ceramic, stone and clay products	620	260	(41.9)	51	(19.6)	42	(16.2)	15	(5.8)	62	(23.8)	42	(16.2)
Iron and steel	339	99	(29.2)	19	(19.2)	18	(18.2)	1	(1.0)	17	(17.2)	16	(16.2)
Non-ferrous metals and products	287	123	(42.9)	28	(22.8)	22	(17.9)	9	(7.3)	18	(14.6)	18	(14.6)
Fabricated metal products	931	376	(40.4)	69	(18.4)	59	(15.7)	11	(2.9)	64	(17.0)	44	(11.7)
General machinery	1542	801	(51.9)	127	(15.9)	109	(13.6)	31	(3.9)	117	(14.6)	130	(16.2)
Electrical machinery, equipment and supplies	2099	1065	(50.7)	224	(21.0)	184	(17.3)	66	(6.2)	173	(16.2)	158	(14.8)
Transportation equipment	1419	626	(44.1)	129	(20.6)	111	(17.7)	31	(5.0)	87	(13.9)	104	(16.6)
Precision instruments and machinery	584	338	(57.9)	96	(28.4)	91	(26.9)	15	(4.4)	74	(21.9)	64	(18.9)
Ordnance and accessories	17	13	(76.5)	5	(38.5)	5	(38.5)	1	(7.7)	4	(30.8)	6	(46.2)
Miscellaneous	499	248	(49.7)	57	(23.0)	53	(21.4)	17	(6.9)	25	(10.1)	40	(16.1)
Total	14070	6281	(44.6)	1315	(20.9)	1150	(18.3)	296	(4.7)	950	(15.1)	834	(13.3)

Note: In parentheses are, for *IRD*, the percentage to the whole sample; and, for *CRD, CRDN, CRDA, JRD*, and *TA*, the percentages to the number of firms with positive *IRD*.

Appendix Table 2. Mean R&D Intensity (In-house and Procured) by Industry

	All Firms (n = 14070)						Firms with *RDD* = 1 (n = 6648)						
	IRD	*CRD*	*CRDN*	*CRDI*	*JRD*	*TA*	*IRD*	*CRD*	*CRDN*	*CRDI*	*JRD*	*TA*	n
Food	0.267	0.008	0.005	0.003	0.002	0.002	0.619	0.019	0.011	0.008	0.004	0.005	555
Beverages, tobacco and feed	0.351	0.013	0.006	0.007	0.001	0.013	0.653	0.024	0.012	0.013	0.001	0.025	151
Textile mill products	0.412	0.084	0.035	0.048	0.004	0.001	0.996	0.202	0.086	0.117	0.011	0.003	154
Apparel and other finished products	0.119	0.014	0.012	0.002	0.001	0.000	0.614	0.070	0.060	0.010	0.008	0.002	101
Lumber and wood products	0.063	0.003	0.003	0.000	0.001	0.000	0.296	0.015	0.015	0.000	0.006	0.002	32
Furniture and fixtures	0.253	0.012	0.012	0.001	0.001	0.010	0.564	0.027	0.026	0.002	0.003	0.022	79
Pulp, paper and paper products	0.168	0.005	0.001	0.004	0.002	0.017	0.748	0.021	0.005	0.016	0.008	0.077	85
Printing and allied industries	0.067	0.004	0.002	0.002	0.001	0.005	0.461	0.029	0.016	0.013	0.004	0.037	114
Chemical and allied products	2.995	0.263	0.221	0.041	0.007	0.096	3.640	0.319	0.269	0.050	0.008	0.116	714
Petroleum and coal products	0.873	0.028	0.025	0.003	0.003	0.043	1.218	0.039	0.035	0.004	0.004	0.061	43
Plastic products	0.571	0.030	0.018	0.013	0.003	0.010	1.256	0.067	0.039	0.028	0.007	0.023	296
Rubber products	1.209	0.050	0.023	0.027	0.008	0.007	1.957	0.081	0.037	0.044	0.013	0.012	97
Leather tanning, leather products and fur skins	0.703	0.042	0.042	0.000	0.003	0.000	1.501	0.089	0.089	0.000	0.007	0.000	22
Ceramic, stone and clay products	0.561	0.035	0.024	0.012	0.008	0.017	1.195	0.075	0.050	0.025	0.017	0.036	291
Iron and steel	0.219	0.003	0.002	0.001	0.002	0.004	0.694	0.008	0.006	0.002	0.006	0.012	107
Non-ferrous metals and products	0.490	0.044	0.034	0.010	0.003	0.031	1.050	0.095	0.073	0.022	0.006	0.065	134
Fabricated metal products	0.428	0.029	0.013	0.016	0.005	0.008	0.988	0.066	0.030	0.037	0.012	0.019	403
General machinery	0.911	0.039	0.019	0.020	0.005	0.034	1.654	0.070	0.035	0.036	0.008	0.061	849
Electrical machinery, equipment and supplies	1.275	0.073	0.047	0.026	0.004	0.030	2.394	0.138	0.089	0.049	0.008	0.055	1118
Transportation equipment	0.721	0.034	0.021	0.012	0.002	0.024	1.560	0.073	0.046	0.027	0.003	0.052	656
Precision instruments and machinery	1.713	0.073	0.051	0.022	0.008	0.048	2.748	0.117	0.082	0.035	0.013	0.076	364
Ordnance and accessories	1.969	0.041	0.027	0.014	0.001	0.108	2.575	0.054	0.035	0.019	0.002	0.142	13
Miscellaneous	0.819	0.057	0.042	0.016	0.003	0.040	1.513	0.106	0.077	0.029	0.006	0.075	270
Total	0.823	0.051	0.035	0.016	0.004	0.024	1.742	0.108	0.074	0.034	0.008	0.051	6648

Note: The figures show the percentages to sales of respective R&D variables, except n which is the number of firms with *RDD*>0 for each industry.

Appendix Table 3. Summary Statistics by Industry

Industry	*RDINT*	*LSALE*	*VI*	*DIV*	*CFS*	*PC*	*APPRO*	*FLOWS*	*FLOWT*	*SPEED*
Food	0.003	8.266	0.253	0.131	0.030	0.231	0.242	0.363	0.341	2.878
Beverages, tobacco and feed	0.004	9.250	0.198	0.192	0.042	0.238	0.268	0.361	0.348	2.927
Textile mill products	0.004	7.774	0.334	0.109	0.043	0.237	0.264	0.334	0.453	2.881
Apparel and other finished products	0.001	7.581	0.311	0.097	0.018	0.244	0.413	0.350	0.394	3.207
Lumber and wood products	0.001	8.201	0.203	0.140	0.022	0.311	0.420	0.351	0.391	3.222
Furniture and fixtures	0.003	7.984	0.260	0.130	0.029	0.165	0.420	0.351	0.391	3.220
Pulp, paper and paper products	0.002	8.293	0.260	0.128	0.048	0.282	0.206	0.372	0.482	2.904
Printing and allied industries	0.001	8.174	0.351	0.079	0.049	0.167	0.258	0.400	0.623	3.094
Chemical and allied products	0.030	8.943	0.290	0.177	0.059	0.305	0.441	0.456	0.454	2.906
Petroleum and coal products	0.009	10.152	0.191	0.180	0.050	0.383	0.370	0.407	0.417	2.469
Plastic products	0.006	8.372	0.264	0.133	0.049	0.338	0.331	0.279	0.497	2.895
Rubber products	0.012	8.347	0.309	0.162	0.042	0.306	0.334	0.272	0.499	2.886
Leather tanning, leather products and fur skins	0.007	7.707	0.265	0.095	0.012	0.234	0.414	0.348	0.396	3.195
Ceramic, stone and clay products	0.006	8.178	0.301	0.171	0.050	0.276	0.284	0.430	0.433	2.708
Iron and steel	0.002	8.758	0.232	0.087	0.037	0.289	0.265	0.408	0.477	2.404
Non-ferrous metals and products	0.005	8.514	0.266	0.122	0.055	0.380	0.297	0.368	0.387	3.026
Fabricated metal products	0.004	8.174	0.301	0.118	0.044	0.215	0.341	0.394	0.544	3.206
General machinery	0.009	8.300	0.314	0.135	0.045	0.224	0.348	0.430	0.492	3.125
Electrical machinery, equipment and supplies	0.013	8.569	0.307	0.141	0.046	0.406	0.319	0.373	0.455	3.360
Transportation equipment	0.007	8.670	0.297	0.159	0.048	0.280	0.317	0.359	0.508	3.122
Precision instruments and machinery	0.017	8.414	0.327	0.228	0.045	0.301	0.347	0.500	0.454	3.120
Ordnance and accessories	0.020	10.289	0.319	0.324	0.050	0.176	0.369	0.388	0.466	3.129
Miscellaneous	0.008	8.519	0.277	0.216	0.037	0.242	0.383	0.357	0.427	3.182
Total	0.008	8.407	0.293	0.143	0.044	0.280	0.322	0.385	0.463	3.064

Notes: No. of observations = 14070.

(Preliminary)

R&D and market value: appropriability vs. preemption[1]

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Summary

The recent empirical studies on innovation and market value suggest that R&D has a strong complementarity with market share in the market valuation of firms. Blundell, Griffith and Reenen (1999) argue that it represents the strategic preemptive effect, while Hall and Vopel (1997) suggest a Schumpeterian reason (the cost of financing R&D is lower for large firms). The theoretical framework of these studies is the classical work by Griliches (1981), which postulates that the market value of a firm is given by the sum of the values of physical capital and R&D capital with respective multipliers. However, non-rivalry in using new knowledge within a firm makes this framework highly questionable. This paper examines the nexus between R&D and market value, based on a structural model addressing this problem. Major findings are the following. First, a structural model shows that the market evaluation of R&D may well be high for a firm with a large market share, simply due to its appropriability advantage. Second, our estimation based on the data of the Japanese firms shows that the new specification does better. Third, it shows that there is no statistical support for the prevalence of preemption effect.

Key words: R&D; market valuation; appropriability; preemption

JEL classification: L10, O32

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I. Introduction

The recent empirical studies on R&D and market value suggest that R&D has a strong complementarity with market share in the stock market valuation of firms[i]. More specifically, while a firm with a large market share tends to enjoy high market valuation of both tangible and R&D investments, such effect looks to be especially strong for R&D investment. Such relationship was first pointed out by Blundell, Griffith and Reenen (1999) based on their study of British manufacturing firms for the time period of 1972-1982. They found that the interaction term between market share and R&D variable had a significantly positive coefficient in explaining the market value of a firm, even controlling the effects of market share and R&D individually. Hall and Vopel (1997) confirmed such relationship, based on their study of US firms for the time period form 1987-1991, although Toivane, Stoneman and Bosworth (2002) did not find it from the more recent (1989-1995) data of UK firms. Blundell, Griffith and Reenen (1999) argue that their finding that the marginal return of R&D is high for a firm with large market share represents the strategic preemption effect or efficiency effect (Gilbert and Newbery (1982)). Hall and Vopel (1997) suggest a Schumpeterian reason (the cost of financing R&D is lower for large firms), given their finding that the marginal return of R&D depends more on firm size than on market share[ii].

These studies, however, may have the following fundamental problem. Their estimation is based on the model of market value determination, which treats R&D investment in the same manner as ordinary investment. In particular, they are based on the classical work by Griliches (1981), which postulates that the market value of a firm is given by the sum of the values of physical capital and R&D

capital with respective multipliers. However, knowledge created by R&D investment has a unique characteristic that the expansion of the use of knowledge within a firm costs nothing, unlike investment in plant and equipment. Consequently, the linear homogeneity assumption of the profit function which is an essential assumption of the concept of the capital aggregate (Hayashi and Inoue (1991)) does not hold, when the capital of a firm consists of both knowledge and ordinary capital. Thus, the above market power interpretations of the R&D, market power and market value nexus may depend on a wrong underlying model.

This paper attempts to investigate this nexus by developing a structural model of market value determination as well as by providing new estimates based on that model. First, it presents a simple structural model, which explicitly takes into account the non-rivalry in using knowledge within a firm. The model shows that the stock market evaluation of R&D can be high for a firm with a large market share, simply due to its appropriability advantage. Second, it estimates the model explaining the market value of a firm, based on both conventional specification due to Griliches (1981) and on the new specification, using the data of the Japanese firms (1991-2000). It shows that the new specification does better than the conventional one in explaining the market value of a firm. While it confirms that the relationship as identified by Blundell, Griffith and Van Reenen (1999) holds for the Japanese industry, it also shows that the interaction term between market share and R&D has a smaller coefficient for the sub-sample of the firms with largest market shares. Third, we evaluate the effect of interaction term between market share and R&D, based on the "true" model of market value determination, and finds that a firm with larger market share has actually a lower return from R&D.

The rest of the paper is organized in the following manner. Section II presents an analytical framework. Section III discusses empirical specification and data and section IV presents the estimation results and discuss them. Section V concludes.

II. Analytical framework

First, let us describe the conventional specification, the origin of which is Griliches (1981). The market value of a firm is given by the following specification.

$$V = \theta(K + \lambda IK) \qquad (1)$$

where K is the value of tangible capital stock, IK is the value of intangible capital stock, λ is the relative shadow price of intangible asset, and θ represents the divergence between the market value of a firm and the sum of its tangible and intangible capital stocks. θ reflects both the monopoly position of a firm and the risk it faces. Defining Tobin's q as the market value relative to the tangible capital stock ($q = V / K$),

$$q = \theta(1 + \lambda IK / K) \qquad (2)$$

Taking the logarithms of both sides, and assuming that $\lambda IK / K$ is significantly less than 1, we have

$$\ln q = \ln(V / K) \cong \ln\theta + \lambda IK / K \qquad (3)$$

In this framework a firm with high market power can generate more profit from both tangible and intangible capital stocks. Reflecting this, empirical studies postulate that market share appears as one determinant of the determinants of θ (see, for an example, Jaffe (1986), Blundell, Griffith and Van Reenen (1999) and Toivane, Stoneman and Bosworth (2002)). If a firm can generate profit from its intangible capital stock on top of this effect, the market share would also increase λ. Blundell, Griffith and Van Reenen (1999) finds evidence consistent with this, and argue that is supports the preemptive motivation of R&D, given that the appropriability advantage of a firm with market power is being controlled through its effect on θ.

As an alternative to the above specification, we consider the following structural model, which explicitly takes into account the effect of R&D investment different from that of investment in plant and equipment. We consider a two-period model for simplicity. Both tangible and intangible investments are made in the first period and output is produced in the second period. c represents constant marginal capital cost of production, p is the market price (net of material, utility and labor costs), y is the output, K is tangible capital stock at the end of the first period (investment in the first period), IK is the intangible capital stock at the end of the first period (investment in the first period), π is the profit in the second period, V is the market value of the firm at the end of the first period. The tangible capital stock K at the end of the first period is given by

$$K = cy \qquad (4).$$

Assuming that interest rate is zero for simplicity, we have

$$\Pi = (p - c)y - IK = py - K - IK \qquad (5)$$

$$V = py = K + IK + \Pi \qquad (6).$$

Tobin's q in this specification is given by

$$q = V / K = py / cy = p / c \qquad (7)$$

c stands for the unit cost of production, which does not include R&D or the other intangible costs. The price cost margin of a firm (p/c) tends to increase with its R&D

investment, since such firm can win more in innovation races, and it can have higher quality and/or lower cost of production (see the Appendix for more elaborations). Taking into accounts of the diminishing return of such investment as well as the negative effect of more supply on price, we have the following specification of Tobin's q of the firm:

$$q = 1 + (p - c)/c = 1 + \beta_0 + \beta_1 IK - 1/2\beta_2 (IK)^2 - \beta_3 K \quad (8).$$

We absorb the effects of investments by competitors by constant term. We expect that $\beta_1 > 0$, $\beta_2 > 0$ and $\beta_3 > 0$. Here we have an implicit assumption that the firm appropriates the return from its intangible investment only from using the knowledge for its production. Combining equations (7) and (8), we have

$$V = K(1 + \beta_0 + \beta_1 IK - 1/2\beta_2 (IK)^2 - \beta_3 K) \quad (9)$$

Although K and IK are jointly determined to maximize V, K is partially exogenous, reflecting such non-R&D factors as cost of acquiring K and location or resource based advantages in production.

There is an important difference between equations (2) and (8) (or between equations (1) and (9)). What mattes in the determination of q is the ratio between intangible capital stock and tangible capital stock in the specification (2), while it is the absolute level of intangible capital stock according to (8). To put it in another way, what matters in the determination of the market value of the firm is the intangible capital stock according to the specification (1), but it is the product of tangible and intangible capital stocks in specification (9). The difference arises due to the following reason. In our specification, the intangible capital stock or knowledge affects price cost margin, so that its effect on market value depends on the size of production or the tangible capital stock of a firm. Thus, a large firm has an appropriability advantage. On the other hand, intangible capital stock is treated as an addition to tangible capital stock in the Griliches specification, reflecting its basis on a accounting formula, so that the above interaction is lost.

Specification (8) (or (9)) provides a straightforward explanation why the stock market evaluation of R&D is found to be high when a firm has a large market share. This is based on the appropriability advantage of such firm: the firm with large tangible capital stock (thus, a firm with a large market share in an industry) can more effectively translate the knowledge created by intangible capital stock in the profit, although we have to note that the level of tangible capital stock is endogenous to intangible investment. Thus, it is unnecessary for us to resort to the preemptive motivation of a firm for explaining the larger effect of R&D investment of the firm with a larger market share.

In the long run equilibrium the profit will be dissipated though competition (investment and entry). If such dissipation is perfect, price is equal to average cost[iii]. Assuming this, the longrun Tobin' q (q_{LR}) is given by

$$q_{LR} = V / K = 1 + IK / K \qquad (10)$$

Thus, what determines q in the longrun in this case is the ratio between intangible capital and tangible capital. Equation (10) is identical to Equation (3) when both λ and θ are unity. Thus, if this longrun relationship also prevails, the rejection of equation (3) in favor of equation (8) would become difficult. However, if we focus on short-run changes over time such as within-firm variation in a few years time interval, equation (3) or (8) would still hold while equation (10) would be less binding. Thus, panel estimation with fixed effects would help us to identify equation

(3) and equation (8). On the other hand, cross section estimation may provide biased support to equation (3), since missing variables such as management capability may be more correlated with the relative R&D investment than with the absolute level of R&D.

III. Empirical specification and data

In this section, first, we evaluate which of the models (equation (3) and equation (8)) better explain the market value of a firm. Second, we estimate the model based on the conventional specification by classifying the sample into three sub-samples according to market shares. Since the preemption motivation would be important only for a firm with market power, the interaction term between market share and R&D variable would be more significant for the sub-sample of the firms with the largest market shares if it indicates preemption effect. Third, given the support to the new specification, we investigate whether a firm with a larger market share earns more from R&D investment, using this specification.

3.1 Hypothesis and specifications

The conventional specification of the Tobin' q ($q_{i,t} = V(K_{i,t}, IK_{i,t})/K_{i,t}$) based on equation (3) uses the logarithm of the value of tangible assets ($\ln K_{i,t}$), the ratio between intangible asset and tangible asset ($(IK/K)_{i,t}$), and the firms' market share ($MS_{i,t}$) as independent variables:

$$\ln q_{i,t} = (\sigma - 1)\ln K_{i,t} + \beta_1 MS_{i,t} + \beta_2 (IK/K)_{i,t} + u_t + \varepsilon_{i,t} \qquad (11)$$

σ is a parameter indicating the scale economy of production(if there is economy of scale in production, σ exceeds one).The market share is used to measure the profitability of the assets due to the existence of market power. u_i is the unobserved firm-level fixed effect and the $\varepsilon_{i,t}$ is the error term. We generalize this specification, so that it can cover the equation (8) as well.

$$\ln q_{i,t} = (\sigma-1)\ln K_{i,t} + \beta_1 MS_{i,t} + \beta_2 (IK/K)_{i,t} + \beta_3 IK_{i,t} - 1/2\beta_4 (IK_{i,t})^2 + u_i + \varepsilon_{i,t} \qquad (12)$$

We absorb the last term of equation (8) by the first term of this equation, so that σ in this specification reflects both economy of scale in production and demand elasticity. If the correct model is equation (8) rather than equation (3), we would find that β_2 is insignificant while β_3 is significant. If the reverse is the case, specification (3) is supported.

We also estimate the following model which is used by Blundell, Griffith and Reenen (1999) to evaluate the Gilbert and Newbery hypothesis.

$$\ln q_{i,t} = (\sigma-1)\ln K_{i,t} + \beta_1 MS_{i,t} + \beta_2 (IK/K)_{i,t} + \beta_5 (MS^* IK/K)_{i,t} + u_i + \varepsilon_{i,t}$$

We allow β_5 to vary across the sub-samples with different level of market shares Since the preemptive motive would be important for the firms with significant market power, we would find that β_5 is significantly larger for the sub-sample of the firms with largest market shares, assuming that the model as represented in equation (3) is correct. Finally, assuming that equation (8) is a correct model, we estimate the following model to investigate whether the firm with larger market share in fact earns more from R&D:

$$\ln q_{i,t} = (\sigma-1)\ln K_{i,t} + \beta_1 MS_{i,t} + \beta_3 IK_{i,t} - 1/2\beta_4 (IK_{i,t})^2 + \beta_6 (MS^* IK)_{i,t} + u_i + \varepsilon_{i,t}$$

In particular, if the preemption motivation is significant and is realized, we would find that β_6 is positive and significant.

In estimating these equations, we use fixed effect estimation, since it is very likely that the error term ε_i is positively correlated with independent variables (The firm with high management capability would be able to undertake more R&D investment, for an example). In addition, we introduce yearly dummies as well as industry by year dummies to control the effects of macroeconomic or industry-wide changes on the stock market price.

3.2 Data

We have three matched data sources. The data on the financial structure of the firms are from the NEEDS database (Nikkei Electronic Economic Database Systems) which uses mainly the annual financial reports by the firms to the financial regulatory authority of Japan. Information on R&D investment and advertisement as well as the sales of a firm by segments are from the Basic Survey of Business Structure and Activity (Kigyoukatsudou-kihonn-chousa) by the Ministry of Economy, Trade and Industry, which cover extensively manufacturing sector and distribution sector, but also other sectors to a very limited extent. Since the available Surveys were only those conducted in 1991FY, 1994FY and every year thereafter up to 2000 FY, we use four data points (1991, 1994, 1997 and 2000 fiscal years). The information on market value of a firm is from the Worldscope database. The timing of stock market information is chosen so that the stock market fully assimilates the financial and business information of a particular fiscal year. In particular, the market value of a firm as of the end of the next calendar year (mostly

9 months after the closure of the fiscal year) is chosen to correspond to the financial status and business activities of the firm of the fiscal year which mostly end on the March 31st (e.g. The market value as of the end of 2001 corresponds to financial status as of the end on the March 31st 2001 and the business activities of the 2000 fiscal year ending on the March 31st 2001).

(1)Value of tangible asset ($K_{i,t}$): We use the total asset of a firm[iv]. Since most firms do not capitalize R&D and advertising expenditures, these expenditures and the total asset are mutually exclusive contributions to the market value of a firm in most cases. Since we use the book values for the total asset and the debt of a firm due to our data constraint[v], we introduce the structure of the assets to control the variation of the divergences between the book value and the market value across different types of assets.

(2) Market value of firm and Tobin's q ($MV_{i,t}$ and $q_{i,t}$): The market value of a firm is defined as the sum of the total market capitalization of a firm as of the end of the calendar year and the book value of its debt.

(3) Structure of the total assets: The variables we use for controlling the divergence between the book value and the market value are the current asset ratio ($ca_{i,t}$=current asset/total asset), the proportion of the financial investments ($inva_{i,t}$=financial investments/total assets), the proportion of land ($land_{i,t}$=land/total assets), and debt asset ratio ($debtasset_{i,t}$). Since the value of land dropped significantly in Japan in 1990s, the proportion of land in the total assets is expected to affect the market value of a firm significantly.

(4) Intangible investments ($IK_{i,t}$): We distinguish two types of intangible capital:

R&D ($rd_{i,t}$) and advertisement($adv_{i,t}$). R&D of a firm is the sum of the investment internally implemented and that outsourced. Since the length of data available for this study is limited, we use flow value of R&D in stead of stock value. The past studies by Hall (1993a, 1997) suggest that these two measures do not have much difference in explaining the market value of a firm (the flow value often has a higher explanatory power).

(5) Market share ($MS_{i,t}$) : The market is defined at three-digit industry level (59 industries for manufacturing sector and 152 industries for all sectors) and the market share of a firm is defined as the ratio between the sales (domestic and export sales) of each firm and the sum of the sales of all firms covered by the Basic Survey of Business Structure and Activity. Although the Basic Survey is compulsory, it neither covers small firms nor imports. However, since we introduce industry by year dummies as independent variables and use firm-level fixed effect estimation, we can mostly avoid biases due to the incomplete coverage of the survey. When a firm operates in more than one industry, we use a weighted average of its market shares, with its sales in each industry segment as a weight.

Our sample is an unbalanced panel, consisting of 2,367 firms, with 102 industry affiliations in total and covering four years with three year interval. 1,353 firms belong to the manufacturing sector, with 57 industry affiliations. The summary statistics are provided in Table 1.

(Table 1)

IV. Estimation results

Table 2 shows four estimation results based on equation (12). Estimation 1 in the Table shows that the R&D investment as well as its square is highly significant while the R&D investment relative to the total asset (relative R&D investment) is insignificant. Thus, the estimation results strongly support equation (8) and rejects equation (3). The significantly negative coefficient of the R&D investment squared suggests a diminishing return on R&D investment within a firm for a given time period. Advertisement investment variables do not have significant coefficients. The coefficient of the tangible capital is negative and significant, although it is relatively small (-0.1). It may reflect diseconomy of scale in productions and/or the negative response of price to the expansion of supply.

(Table 2)

Estimation 2 and 3 are robustness checks. Estimation 2 has the sample restricted to the manufacturing sector, and Estimation 3 has the sample restricted to those firms which did R&D for all four years. The estimation results are highly consistent with Estimation 1. The absolute level of R&D investment is highly significant, while its relative level is no significant. There are two differences. One is higher significance of the advertising investment relative to the total asset. In these estimations, the relative advertisement expenditure, rather than its absolute level, matters unlike the case of R&D investment. The second difference is that the coefficient of the tangible capital is positive and significant for the consistent performers of R&D (Estimation3). Finally, Estimation 4 shows the results of random effect estimation. We added the logarithm of firm age as another control variable of the firm heterogeneity. In this estimation both the absolute and relative levels of R&D investment are highly significant. The significance of the relative R&D investment, however, is very likely to be caused by the correlation between missing variables and the relative R&D investment.

Let us turn to the estimation results based on specifications (13) and (14) (see Table 3). Estimation 5 confirms that the relationship as identified by Blundell, Griffith and Van Reenen (1999) holds for the Japanese industry. The interaction term of market share and R&D investment has a highly significantly positive coefficient. Thus, if equation (3) is a true model, this result shows that a firm with larger market share gains more from R&D investment, which is consistent with efficiency effect. However, the next estimation (Estimation 6) shows that the coefficient of the interaction term is the smallest for the sub-sample of the firms with the top 10% firms in terms of market shares. Thus, the above interpretation is clearly misguided by the wrong specification of the model. The positive coefficient of the interaction term as observed in Estimation 5 can be explained easily by equation (8). Since market share is likely to be nearly proportional to the level of tangible capital of a firm for a given industry, we have the following relationship:

$$MS^{*} IK/K \approx \alpha K^{*} IK/K = \alpha IK \qquad (15)$$

This is nothing but the third term of equation (8). That is, the interaction term is very likely to have simply picked up the effect of R&D investment on the price cost margin. The lower coefficient of the interaction term for the firms with the largest market power may reflect the diminishing return of R&D investment.

(Table 3)

There is a remaining question of whether the preemption effect holds in the "true" model. Estimation 7 offers an answer. According to the estimation based on the "true" model of market value determination, the interaction term between market share and R&D has a negatively significant coefficient. That is, a firm with larger market share has actually a lower return from R&D. Thus, the statistical evidence from market value and R&D investment does not provide support at all to the view that strategic preemptive motivation is prevalent and successful.

V. Conclusion

This paper may have the following two contributions. First, we have derived the explicit predictions of a structural model of market value determination (although a very simple one) on the relationship between R&D investment and market value. This has hopefully clarified the pitfall in treating the accounting definitional relationship as a structural equation. Second, we have tested the empirical validity of such structural model. One major implications of this empirical exercise is that the statistical evidence is against the prevalence of preemption effect.

There are a number of research issues to be pursued. One is to understand the difference between R&D and advertisement investments. This paper showed that R&D follows pretty much the structural model presented, while the advertisement investment does not. Moreover, the relative advertisement investment rather than the absolute investment is significant, unlike the case of R&D, for the sample where advertisement investment is significant,. This may indicate that advertisement investment is more to do with delivery of knowledge or information to consumers than to do with their creation. The second issue is to explore the inter industry differences of the relationship between intangible investments and market value, given a different appropriability conditions for an example..

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Appendix Price cost margin and R&D

This appendix illustrates the three important channels by which R&D increases the price cost margin of a firm. The first important channel is high probability of a firm with large R&D to win the patent race and to acquire a patent with a large scope. The winner of the patent race is protected from competition, so that it can set high price. Competition is more restricted when the firm has obtained a patent with a large scope. Even if patent protection is not granted, a firm moving quickly in innovation race can keep market power for a longer period. Thus, R&D investment enhances the probability of winning the innovation race and the amount of reward when it wins.

The second and third channels are quality advantage and cost advantage in competition. Let us assume that firm A can produce a good with quality z in terms of consumers surplus for marginal cost c, while its competitor produces a good with quality z^* for cost c^*. Bertrand competition between the two firms forces them to set the prices p and p^* in the following manner:

$$z - p = z^* - p^* \qquad \text{(a.1)}$$

If we assume that firm A has competitive advantage, its competitor is forced to set its price at its cost ($p^* = c^*$). Thus, the firm A has the following price cost margin:

$$(p - c)/c = \{(z - z^*) + (c^* - c)\}/c \qquad \text{(a.2)}$$

This clearly shows that a firm which improves the quality of its product (z) or reduces its cost (c) by R&D investment has higher price cost margin.

The above results on quality and cost advantages hold for the other models of competition. Let us consider cost advantage in quantity competition with homogeneous goods (i.e Cournot competition). If we assume constant elasticity demand curve, it is well-known that the price cost margin of firm j is given by

$$(p - c_j)/p = s_j / \varepsilon, \qquad \text{(a.3)}$$

where ε is the price elasticity of market demand. Since a firm with lower marginal cost of production has a higher market share, it has to have a larger price cost margin. Thus, cost-reducing R&D investment increases price cost margin. In the case of a linear demand, the price marginal cost margin is given by

$$(p - c_j)/p = 1 - (N+1)c_j / \{1 + \sum c_k\}, \qquad \text{(a.4)}$$

where $1 - p$ is the market demand and N is the total number of firms. It is immediately clear that a firm with lower cost has higher price cost margin.

Let us turn to the case of price competition with differentiated products. Higher quality of the product offered by firm A makes its reaction curve shift out in the diagram of price competition, since the willingness to pay of its consumers increases. The opposite thing will happen to the competitor of firm A. Since the first effect is likely to be more important, the firm which is successful in improving quality by R&D can increase its price, so that its price cost margin increases.

[i] See Hall (1999) for a comprehensive review of the literature on the approaches to using market value to assess innovation performance. There are a number of advantages to use market value as the performance measure of R&D. First, it reflects the assessment of the future impact of past and current R&D, unlike accounting profit. Second, it reflects the assessment of the firm by the third parties, while the accounting profit can be adjusted based on the view of the management (see Fisher and McGowan (1983) for the problems of accounting profit).

[ii] Schumpeter (1942) pointed out a number of potential advantages of a large firm or a firm with a large market share in innovation. Low cost of financing, including its ability to pool risk, is one of them. In addition, such firm may have higher ability to appropriate the benefit of R&D. It may also advantage due to economy of scale or scope of R&D.

[iii] Generally the longrun profit would depend on entry barriers, although Salinger (1984) finds no significant support to the existence of such longrun entry barriers.

[iv] The total asset of a firm covers financial investments such as equity investments and the value of intellectual property rights purchased.

[v] Hall (1993a,b) and Blundell et al. (1999) report that there is no significant difference due to the difference between the book value and constructed value.

Table 1 Summary statistics (Obs 6966)

Variable	Mean	Std. Dev.	q	lnasset	ms	rd	rda	adv	adva	age	ca	inva	land	debtasset
q	1.215	0.917	1											
lnasset	10.742	1.346	0.022	1										
ms	0.013	0.030	0.045	0.506	1									
rd	0.004	0.023	0.052	0.392	0.323	1								
rda	0.017	0.024	0.069	0.204	0.079	0.372	1							
adv	0.001	0.005	0.070	0.463	0.385	0.606	0.173	1						
adva	0.010	0.022	0.050	0.022	0.032	−0.001	−0.042	0.335	1					
age	51.147	14.210	−0.098	0.252	0.125	0.093	0.115	0.072	−0.135	1				
ca	0.560	0.162	0.021	−0.089	−0.106	−0.047	0.053	−0.124	−0.121	0.006	1			
inva	0.156	0.105	0.005	0.281	0.151	0.151	0.018	0.229	0.167	0.014	−0.486	1		
land	0.091	0.077	−0.071	−0.185	−0.081	−0.099	−0.208	−0.035	0.095	−0.194	−0.516	−0.064	1	
debtasset	0.560	0.204	0.004	0.071	0.033	−0.012	−0.122	−0.040	−0.106	0.177	0.039	−0.097	−0.0374	1

Table 2 Estimaion results (I)

Estimation1: Fixed-effects regression				Estimation2:Fixed-effects regression for manufacturing firms				Estimation3 : Fixed-effects regression for consitently R&D performing firms				Estimation4: Random-effects regression			
lnq	Coef.	Std. Err.		lnq	Coef.	Std. Err.		lnq	Coef.	Std. Err.		lnq	Coef.	Std. Err.	
lnasset	-0.099	0.016	***	lnasset	0.036	0.023		lnasset	0.060	0.027	**	lnasset	0.000	0.006	
ms	-0.074	0.240		ms	0.486	0.391		ms	-0.176	0.303		ms	0.249	0.197	
rda	-0.190	0.321		rda	0.270	0.338		rda	-0.292	0.410		rda	0.751	0.249	***
rd	5.516	1.037	***	rd	4.545	1.040	***	rd	6.910	1.499	***	rd	3.159	0.747	***
rd2	-7.637	2.592	***	rd2	-5.567	2.578	**	rd2	-6.215	3.194	*	rd2	-5.718	2.078	***
adva	-0.033	0.467		adva	2.742	0.705	***	adva	1.674	0.905	*	adva	0.868	0.284	***
adv	5.895	4.141		adv	-7.357	5.102		adv	-8.660	8.171		adv	1.722	2.613	
adv2	-13.552	46.256		adv2	70.286	50.482		adv2	180.504	117.515		adv2	37.925	35.483	
												lnage	-0.113	0.016	***
1994	-0.167	0 091	*	1994	-0.095	0.281		1994	-0.247	0.295		1994	-0.187	0.091	**
1997	-0.356	0.088	***	1997	-1.153	0.366	***	1997	-0.923	0.279	***	1997	-0.360	0.086	***
2000	-1.119	0.291	***	2000	-0.131	0.251		2000	-0.746	0.389	*	2000	-0.583	0.344	*
Financial structure	Yes			Financial structure	Yes			Financial structure	Yes			Financial structure	Yes		
Industry dummies				Industry dummies				Industry dummies				Industry dummies	Yes		
Industry by year dummies	Yes			Industry by year dummies	Yes			Industry by year dummies	Yes			Industry by year dummies	Yes		
Number of obs = 6966 Number of groups = 2367 R-sq:within = 0.4866 Obs/group: min = 1 between = 0.0187 avg = 2.9 overall = 0.1060 max = 4 F(308,4291) = 13.21				Number of obs = 4326 Number of groups = 1353 R-sq:within = 0.5083 Obs/group: min =1 between = 0.1192 avg = 3.2 overall = 0.2401 max = 4 F(187,2786) = 15.40				Number of obs = 3421 Number of groups = 961 R-sq:within = 0.5153 Obs/group: min = 1 between = 0.1298 avg =3.6 overall = 0.2087 max = 4 F(254,2206) = 9.23				Number of obs = 6964 Number of groups = 2367 R-sq:within = 0.4752 Obs/group: min 1 between = 0.2219 avg = 2.9 overall = 0.3115 max = 4 Wald chi2(411) = 4535.34			
sigma_u	36415613			sigma_u	.31126491			sigma_u	.36388534			sigma_u	.25992874		
sigma_e	.19421891			sigma_e	.18575946			sigma_e	.19418163			sigma_e	19427914		

***: 1%significant, *:5%signfiicant, *:10% significant

Table 3 Estimaion (II)

Estimation 5: Fixed-effects regression				Estimation 6:Fixed-effects regression (firms with top 10% in market shares)				Estimation 7: Fixed-effects regression			
lnq	Coef.	Std. Err.		lnq	Coef.	Std. Err.		lnq	Coef.	Std. Err.	
lnasset	-0.083	0.016	***	lnasset	-0.086	0.016	***	lnasset	-0.098	0.016	***
ms	-0.626	0.280	**	ms	-0.699	0.281	**	ms	0.099	0.254	
rda	0.324	0.307		rda	-0.146	0.345		rd	5.962	0.996	***
msrda	28.786	6.788	***	msrda	29.376	6.821	***	rd2	-6.678	2.458	***
adva	0.500	0.401		msrda: additonal effect for middle share firms Note2	51.630	26.091	**	msrd	-7.425	3.650	**
				msrda: additonal effect for lowest share firms Note2	488.939	194.631	**	adv	4.442	3.663	
				adva	0.468	0.401		adv2	11.387	45.069	
1994	-0.188	0.091	**	1994	-0.188	0.091	**	1994	-0.168	0.091	*
1997	-0.373	0.089	***	1997	-0.368	0.088	***	1997	-0.356	0.088	***
2000	-1.135	0.292	***	2000	-1.115	0.292	***	2000	-1.151	0.290	***
Financial structure	Yes			Financial structure	Yes			Financial structure	Yes		
Indsutry by year dummies	Yes			Indsutry by time dummies	Yes			Indsutry by time dummies	Yes		
Number of obs = 6966				Number of obs = 6966				Number of obs = 6966			
Number of groups = 2367				Number of groups = 2367				Number of groups = 2367			
R-sq:within = 0.4813 Obs/group: min = 1				R-sq: within = 0.4824 Obs/group: min =1				R-sq: within = 0.4871Obs/group: min =1			
between = 0.0148 avg = 2.9				between = 0.0144 avg = 2.9				between = 0.0205 avg = 2.9			
overall = 0.0964 max = 4				overall = 0.0938 max = 4				overall = 0.1095max = 4			
F(305,4294) = 13.07				F(307,4292) = 13.03				F(307,4292) = 13.28			
sigma_u | .36399399				sigma_u | .36557271				sigma_u | .36340249			
sigma_e | .19514989				sigma_e | .1949896				sigma_e | .19411073			

Note 1. ***: 1%significant, *:5%signfiicant, *:10% significant

Note 2. Top share firms consist of 202 firms, the middle share firms consist of 1149 firms and the lowest share firms consist of 1140 firms.

Japan's corporate and innovation landscape:

Discussion paper for 13 February NISTEP seminar

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Comments welcome.

Japan is a nation where innovation occurs primarily in large established companies. In contrast in the US, a significant proportion of innovation occurs in venture companies and universities. The reasons behind this situation and its implications are at the heart of this study of autarkic innovation in Japan. But although this initial assertion may seem obvious to some readers, especially in light of reports on the difficulties facing Japanese venture companies[1] and barriers to university-industry technology transfer,[2] it requires qualification and supporting evidence.

Unfortunately, clear evidence is not readily available. There are few studies that trace the development history in different countries of new products in the same industry – studies that would permit conclusions as to the relative importance of universities and venture companies in early stages of the development process.

I myself have done this with respect to new pharmaceuticals. The results, described in a recent publication,[3] support the opening statements above. But this still leaves open the question of innovation in other industries.

Another approach might simply be to compare the number of venture companies in the US and Japan. Indeed, the rate of new company formation in Japan has been among the lowest among industrialized countries.[4] Also, the number of Japanese biomedical venture companies and the number of Japanese university start-ups (in all fields of business) and the number of Japanese biomedical venture companies (including ventures that are not university start-ups) are considerably lower than equivalent US numbers – although the Japanese numbers are rapidly increasing, as I will discuss in a following paper. But there is no shortage of small Japanese companies engaged in manufacturing and even new product development, and by the end of the 1990s the Japanese Government had implemented numerous policies to promote the growth of high technology ventures. So in non-pharmaceutical industries, simply comparing numbers of venture and small and medium size enterprises (hereinafter "SMEs," defined for this study as independent companies with not more than 500 employees) without considering their history and business activities, will not give a clear picture of the contribution of venture companies and SMEs to innovation.

A less ideal way to compare innovation between types of organizations to analyze patents - "less ideal" because patents do not always translate into marketable products, and inventors and companies sometimes apply for patents for reasons other than their conviction that the invention has commercial value. Also it is difficult for anyone but a specialist to determine which patents have significant commercial value or represent significant technical achievements. These problems can be partly alleviated by focusing on issued patents rather than patent applications. Successful prosecution of a patent application requires commitment of time and money[5] and either the US Patent and Trademark Office (USPTO) or the Japan Patent Office (JPO) must judge the invention to be new, inventive and useful.[6]

Analysis of patent applications in genomics, proteomics and related applications filed between 1991 and 1999 in the USPTO, JPO and major European countries indicates that, while venture companies accounted for nearly 40% of US applications, they account for only 12% and 6% respectively in Japan and Europe.[7] Conversely, large companies accounted for only about 50% of US applications but 72% of applications in both Japan and Europe.

[Insert Fig. 1 approximately here.]

But again, how representative of innovation in other technical fields is this narrow subfield within biomedicine? It seems that, even for just either the US or Japan alone, few data exist for all industries as a whole or for specific fields of technology other than biotechnology.[8] There is evidence that venture capital backed manufacturing companies are more likely to obtain patents than non-venture capital backed companies across a wide range of industries,[9] but this still leaves unanswered the relative contribution of established companies, venture companies and universities to innovation.

However analysis of patents applicants in narrow technical fields can help us answer this question. Indeed, since both US and Japanese patents are classified according to International Patent Convention (IPC) codes,[10] it is possible to compare internationally patenting in various fields of technology over different time periods. In particular by making reasonable inferences as to where the inventors were working, it is possible to compare quantitatively the locus of innovation.[11]

The following graphs show the percentage distribution of applicants (first assignees) for six technical categories each defined by a small number of IPC codes.

[Insert Figs 2-7 approximately here.]

I chose the categories so as to represent a variety of non-medical technologies that often draw upon frontier knowledge in science or engineering. Details on how these graphs were constructed are in Appendix 1. I cannot claim they are a representative sample of non-biomedical industries. Nevertheless, they probably represent a sufficient variety of industries to suggest fundamental differences in innovation between the US and Japan.

The principal difference is that venture companies and universities account for significant proportions of domestically originating patents in the US, but much smaller proportions of domestically originating patents in Japan. With just a few exceptions, Japanese venture companies appear not to be innovators in high technology fields – in marked contrast to the situation in the US. Of course, there is variation according to technical field in the US. In medical tomography and radiography, innovation appears to occur almost exclusively in large companies such as General Electric. In rewritable electromagnetic recording devices such as DVDs, innovation seem confined to large foreign (mainly Japanese) companies. But in hip and knee prostheses (which often incorporate advances in material science), video cryptography (which involves software and electrical engineering), high energy lithography (especially for integrated circuit (IC) design and manufacture), and ion implantation devices (for doping various materials to improve their performance as, for example, semiconductors), US venture companies account for a significant proportion of innovative activity.

Moreover, despite contraction in the venture capital market beginning in 2000, there is little evidence that their share of innovative activity is declining. But since the filing date for many of the patents issued in 2003 was prior to 2002, it is possible that the negative effects of this contraction are still to be manifest in a future decline in the proportion of patents issued to venture companies.

Conversely in Japan, there is no indication that the proportion of patents issued to venture companies is increasing. Indeed, in rewritable recording and ion beam implantation devices, universities and GRIs seem to account for considerably more patents than venture companies.[12]

I approached this issue different way by sampling the first pages of all US and Japanese patents issued in 2003 and 1995 that contained "micromachine" (マイクロマシン in Japanese) or "nano" (ナノ in Japanese) as a title word or as a fragment of a title word. The inventions reflect a variety of applications of micromachine (including micro-electrical mechanical systems (MEMS)) and nanodevice or nanoparticle technologies.

[Insert Figs 7 & 8 approximately here.]

The pattern is the same – in fact, even starker than when selecting patents according to IPC code. The locus of high technology innovation in Japan appears to be its large established companies. In the US, it appears evenly divided between large, established companies, venture companies and universities – at least judging by numbers of patents.

Both micromachines and nano patents have increased dramatically since 1995, and with the overall increase in US patents, the share of US venture companies has increased while that of US established companies has decreased. In contrast, Japanese venture companies appear to be playing a negligible role. Of the 39 Japanese 2003 nano patents, one was issued to a small chemical company formed in 1951 and one was issued jointly to AIST and a small Japanese pharmaceutical company established in 1955. In contrast, Korean venture companies formed after 1995 accounted for five of these Japanese patents. None of the 15 Japanese 2003 micromachine patents was issued to an SME or a venture company.

One new phenomenon regarding the 2003 Japanese nano patents is that five are co-owned by AIST and an established Japanese company, while six are co-owned by the Japan Science and Technology Corporation (JST) and an established company (either NEC or Toshiba). In Figure 8, each of these co-owned patents is allocated ½ to the established company co-owner and ½ to the category "university or GRI." The AIST co-owned patents most likely reflect inventions arising in AIST laboratories under cooperative research agreements with the co-owners. The JST co-owned patents probably reflect inventions arising in Japanese universities under nanotechnology cooperative research projects most likely jointly funded by the co-owning companies and the Japanese Government. (JST is a MEXT affiliated corporation that is responsible for patenting many of the inventions arising under such cooperative research projects.) This suggests the possibility of Japanese universities and GRIs are contributing more to innovation than in the past. But it also suggests that this contribution occurs usually in cooperation with established companies, not venture companies.

In summary, bearing in mind the qualification suggested by this last finding as well as the caveats about using patents as an indicator of innovative activity, these data generally support the premise of the opening sentence of this paper – Japan is a nation where innovation in frontier fields of science and engineering tends to occur in large established companies, while in the US, venture companies and universities are among the leading innovators in many such fields. Moreover, many of the US companies appear to be aggressively soliciting customers, prominently advertising their patent portfolios as part of this process.

The above analysis is not to argue that universities do not produce knowledge that is vital to industry, that SMEs do not contribute significantly to the Japanese economy, or that venture companies have never flourished in Japan.

The immediate post-war years saw the formation of Sony (1946), Sanyo (1947), Honda (1948) and Kyocera (1959). Sony pioneered innovations in transistor technology and their applications first to radios then to a range of other electronic products. Kyocera (short for Kyoto Ceramics) became a leader in application the application of material science to a variety of electronic and other products. Also during the 1950s and 1960s, Hayakawa Electric transformed itself from a struggling medium size maker of radios and televisions to the world's leading pioneer of liquid crystal and plasma displays, and into the company we know today as Sharp.

In 2000, SMEs accounted for about 89% of employment and 57% of value added in Japanese manufacturing, even higher than thirty years earlier when they accounted for 83% of employment and 47% of value added.[13] However, probably the majority of manufacturing SMEs rely on subcontracting work for most of their business, and approximately one third rely on subcontracting from a single customer.[14]

During Japan's economic boom years, becoming reliant on a single company (or a small number of companies) for most of a company's business often offered advantages such as stable income and access to advanced production technology and management advice. A company that became reliant on one, two or three larger companies for most of its business is called a shita-uke company while the larger company is called its "parent." These terms imply dependency on the part of the smaller company in a way that the English term "subcontractor" does not. To a lesser extent they also imply obligation on the part of the larger company.

But even during the halcyon boom years there were reports of parents pressuring shita-uke companies to supply exclusively to them and then, in times of economic downturn, demanding lower prices while maintaining their own profit margins. There were also reports that parents would craft supply orders very narrowly so that shita-uke companies had few opportunities to develop competence in new areas that might serve the needs of other customers.[15] Since Japan's economic downturn and the transfer of many manufacturing and even development activities to China and other Asian countries, economic pressure on shita-uke companies has increased. Over the past several years corporate bankruptcy rates have exceeded formation rates in manufacturing.

At least one series of case studies suggests that it has been common for large companies to expropriate the technologies of SMEs – either by espionage, infringement (for which damage awards have been relatively low and litigation expensive) or by applying for a large number of patents for relatively minor improvements on the SMEs' inventions.[16] A venture company that invented innovative IC chips that were a key component NTT DoCoMo's iMode handsets agreed that, in return for becoming NTT DoCoMo's sole supplier for these chips, all its future research in this area would be conducted jointly with NTT DoCoMo and that NTT DoCoMo would co-own all resulting inventions. The venture company soon found it could not engage any other customers. After a few years, it abandoned IC chip development, morphed into a services company, and is now in severe financial difficulties.

The mantra of shita-uke companies that have succeeded in the recent trying economic situation has been that it is essential to diversify one's customer base, it is extremely dangerous to remain dependent upon a small number of main customers. Some shita-uke companies are able to make this transformation. Reports in the Japanese business press suggest that gaining contracts with foreign companies have been critical events in allowing a number of shita-uke companies to make this transition successfully. Certain regional self-help associations of venture businesses appear to be fostering the growth of new high technology companies in particular areas.

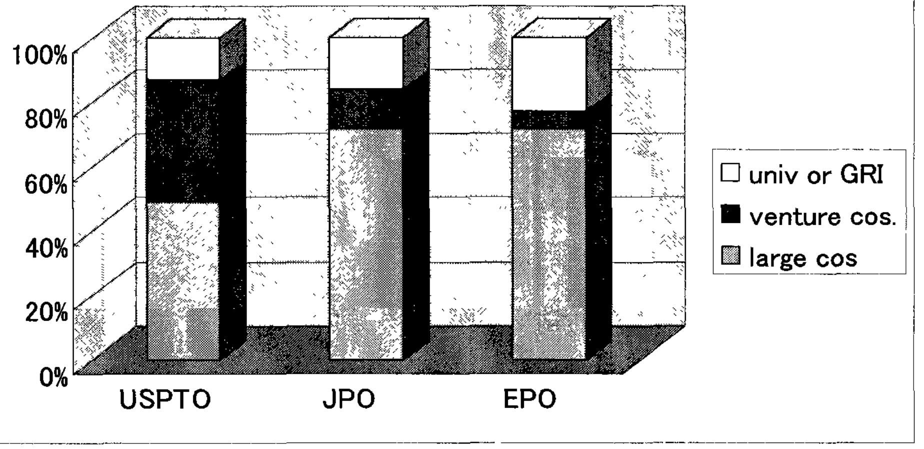
These issues will be discussed further in a following paper. But for this overview of Japan's corporate innovation landscape, these observations hint at partial answers to a question that lies at the heart of this study – why have not more Japanese SMEs (including new venture companies) been able to use technical expertise to attract cooperation from established companies? To frame the question more narrowly, why have not more SMEs been able to use intellectual property rights as leverage to strike deals with established companies that will allow them to grow independently? Or perhaps within the past few years, they have begun to do so. And as a result of sometimes wrenching economic and social adjustments, a fundamental change has begun that will eventually result in venture companies and other SMEs playing more important roles as high technology innovators.

As for innovation in universities, this is the focus of a following paper. Suffice for now to note that industry has always had important informal ties with university researchers. However, the initiative for exploiting and developing university discoveries has, until very recently, lain with industry, specifically with large established companies. Universities had no legal authority, personnel or financial incentives to play a pro-active role in technology development. These factors, in addition to rules governing the ownership and transfer of intellectual property rights, have had their most severe impact on the formation of university start-ups.

The legal framework that has limited cooperation between industry and universities is in the last stages of a fitful dismantling process that began around 1998. Partly as a result, there has been an upsurge of formal cooperative research agreements between industry and universities and an explosion in the number of university start-ups. This latter phenomenon, probably more than any other, is the most significant change on the Japanese innovation landscape.

But the start-up venture boom is fragile. Moreover, a system of distributing university research funds that is still insufficiently informed and objective, and a system of university career advancement that still depends inordinately upon patronage, continue to diminish incentives for university-industry cooperation and entrepreneurial behavior.

Fig. 1. Genomics, proteomics and related applications



Source: JPO (2002)

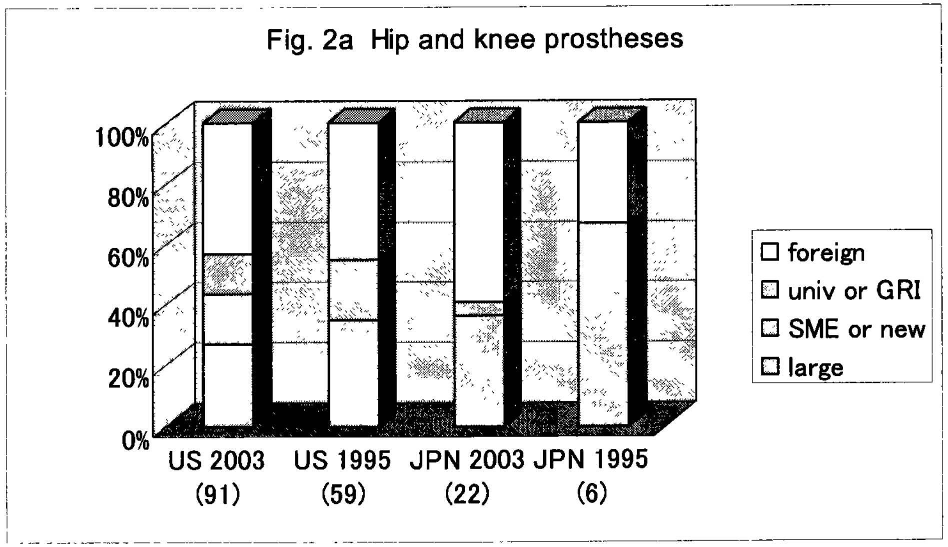


Fig. 2a Hip and knee prostheses
100%
80%
60%
40%
20%
0%
US 2003 (91)
US 1995 (59)
JPN 2003 (22)
JPN 1995 (6)
foreign
univ or GRI
SME or new
large

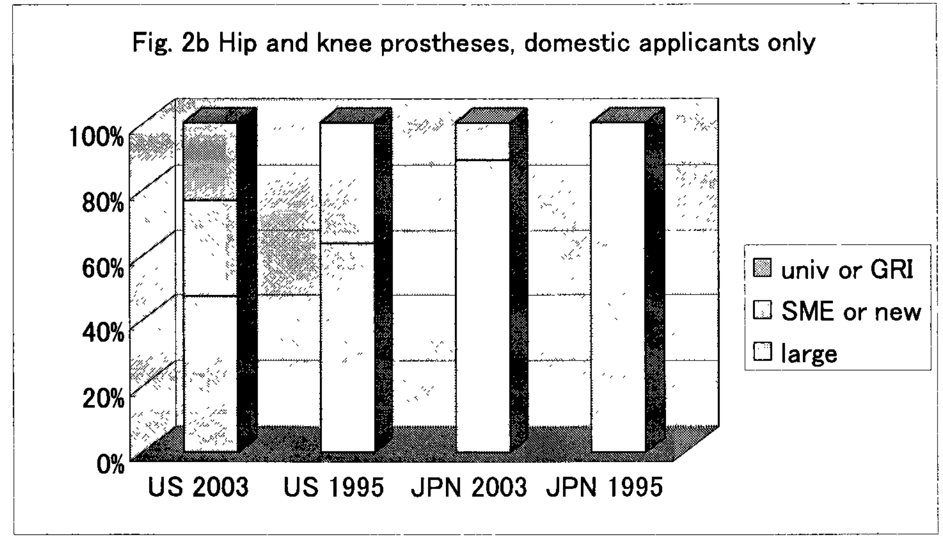


Fig. 2b Hip and knee prostheses, domestic applicants only
100%
80%
60%
40%
20%
0%
US 2003
US 1995
JPN 2003
JPN 1995
univ or GRI
SME or new
large

—87—

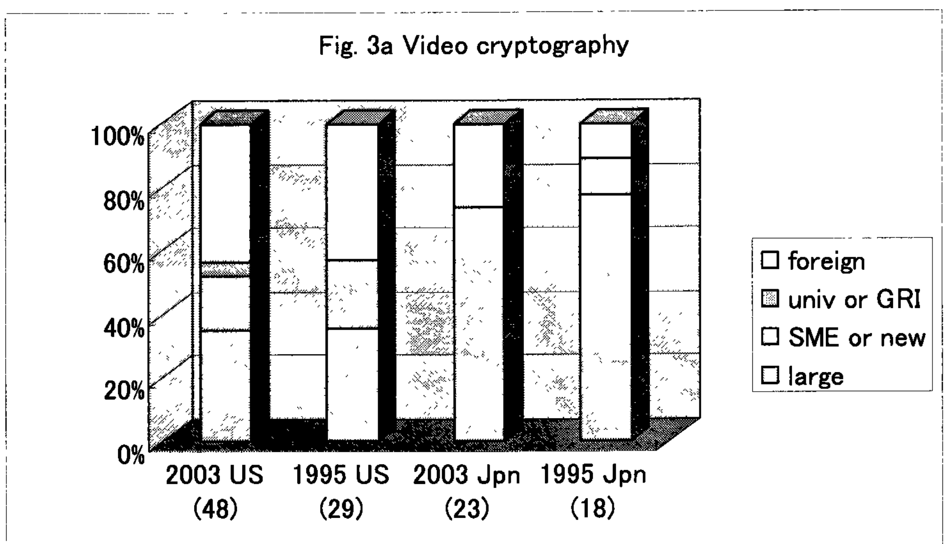


Fig. 3a Video cryptography
100%
80%
60%
40%
20%
0%
2003 US (48)
1995 US (29)
2003 Jpn (23)
1995 Jpn (18)
foreign
univ or GRI
SME or new
large

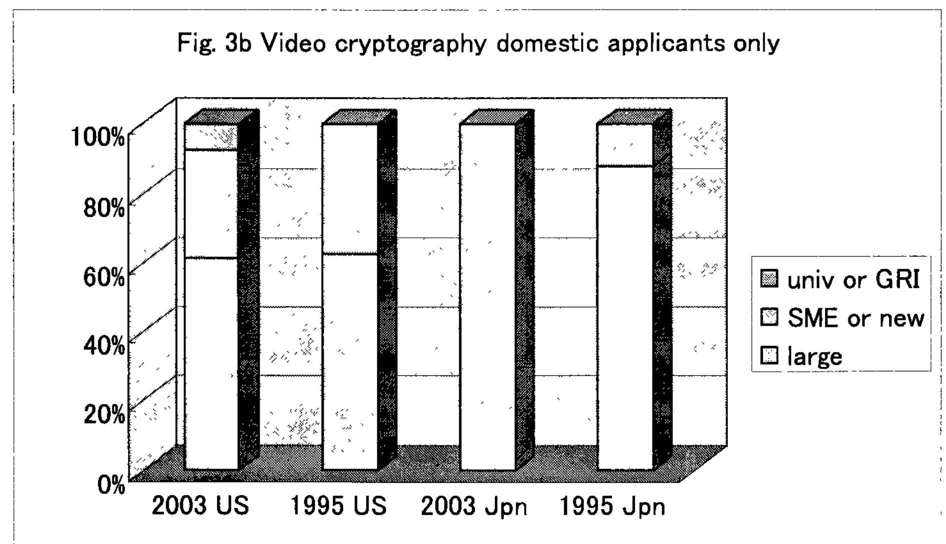
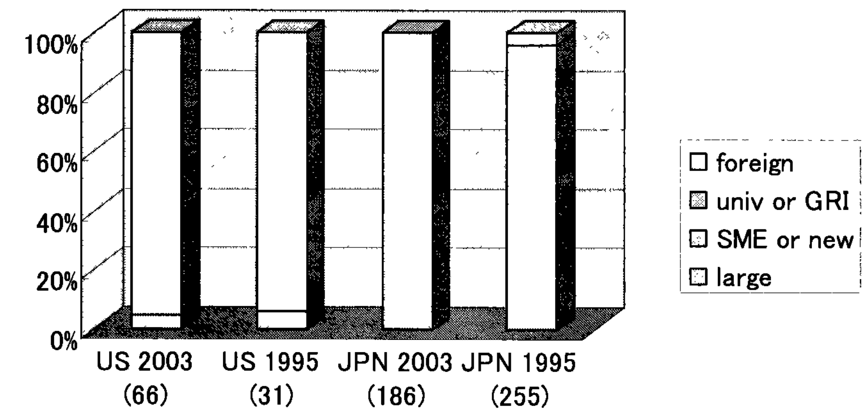


Fig. 3b Video cryptography domestic applicants only
100%
80%
60%
40%
20%
0%
2003 US
1995 US
2003 Jpn
1995 Jpn
univ or GRI
SME or new
large

Fig. 4a Rewritable electromagnetic recording devices



Rewritable elecromagnetic recording devices, domestic applicants only

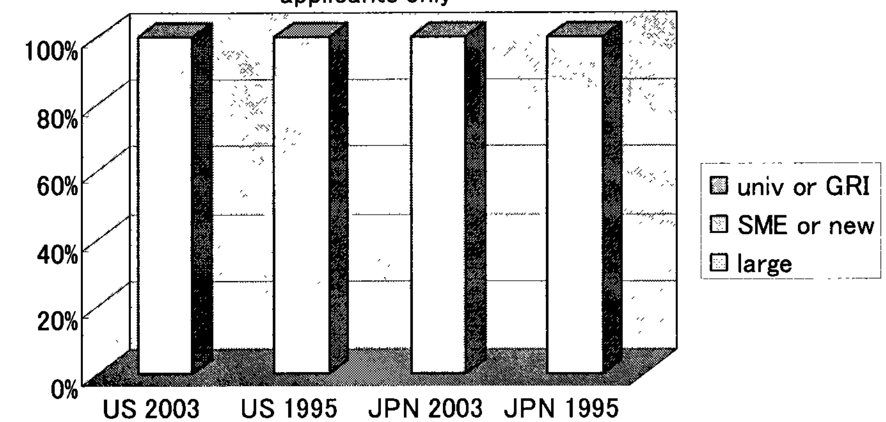


Fig. 5a Tomography and planar medical radiography

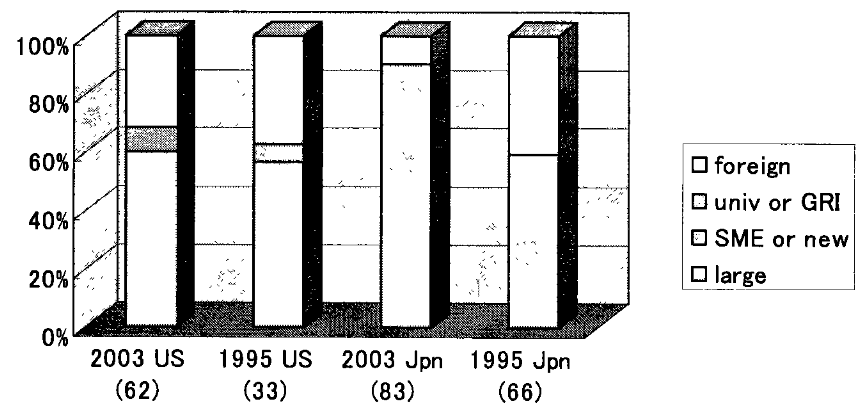


Fig. 5b Tomography and planar medical radiography, domestic applicants only

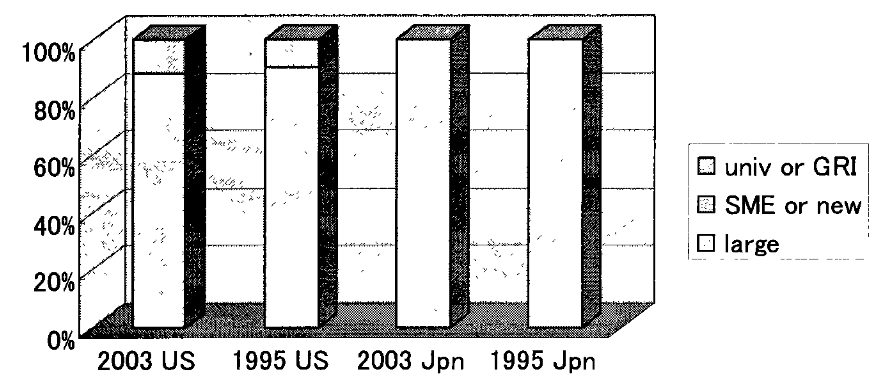


Fig. 6a Irradiation devices, especially for X or gamma ray lithography

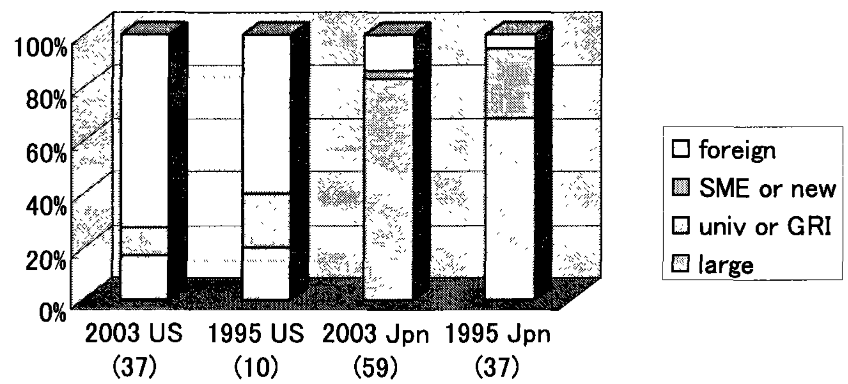


Fig. 6b Irradiation devices, especially for X or gamma ray lithography, domestic applicants only

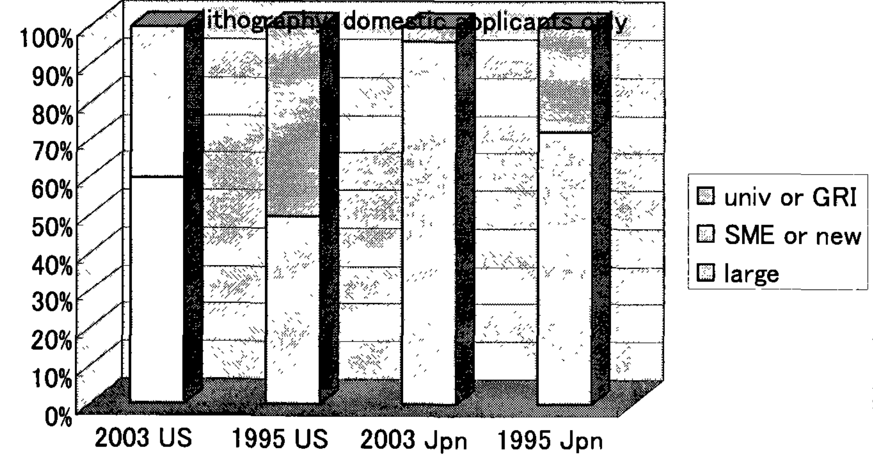


Fig. 7a Ion beam tubes and ion sources

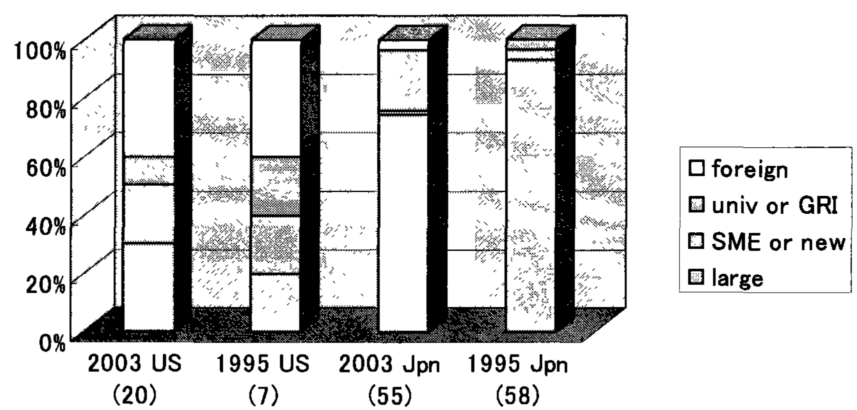
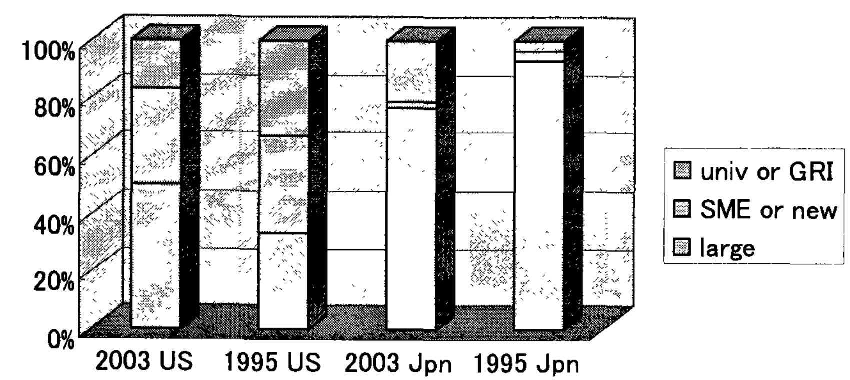


Fig. 7b Ion beam tubes and ion sources, domestic applicants only



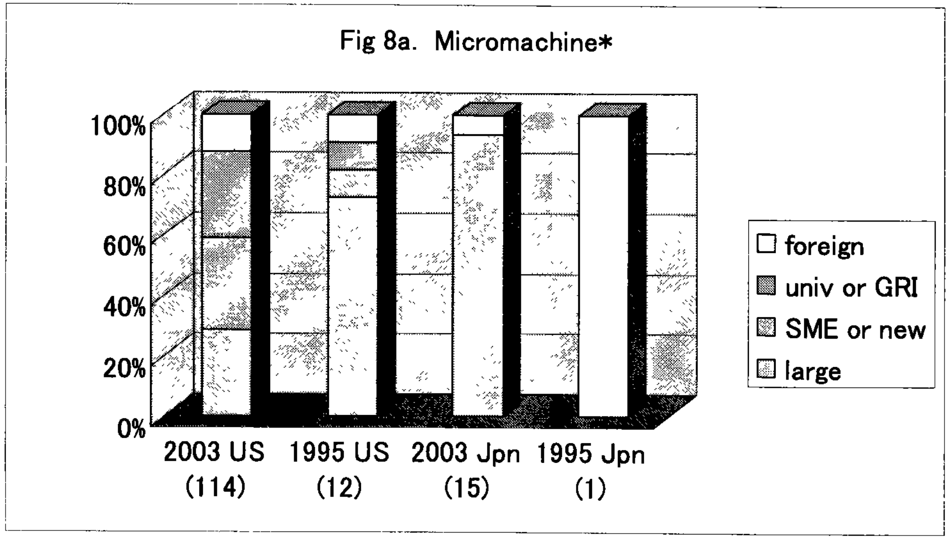


Fig 8a. Micromachine*
100%
80%
60%
40%
20%
0%
2003 US (114)
1995 US (12)
2003 Jpn (15)
1995 Jpn (1)
foreign
univ or GRI
SME or new
large

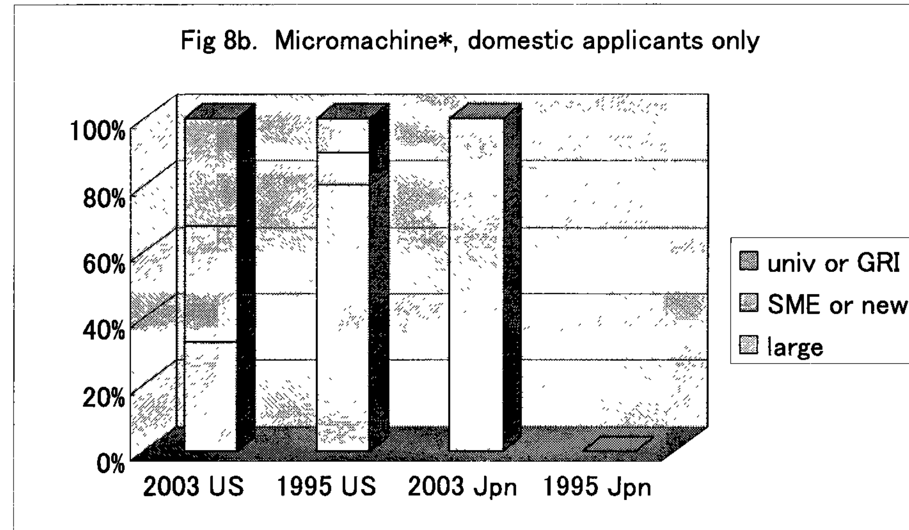


Fig 8b. Micromachine*, domestic applicants only
100%
80%
60%
40%
20%
0%
2003 US
1995 US
2003 Jpn
1995 Jpn
univ or GRI
SME or new
large

—90—

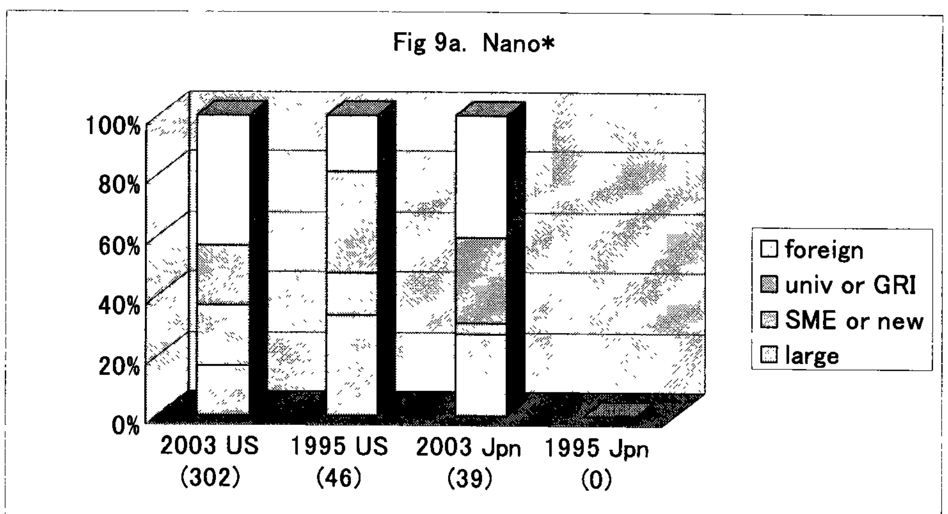


Fig 9a. Nano*
100%
80%
60%
40%
20%
0%
2003 US (302)
1995 US (46)
2003 Jpn (39)
1995 Jpn (0)
foreign
univ or GRI
SME or new
large

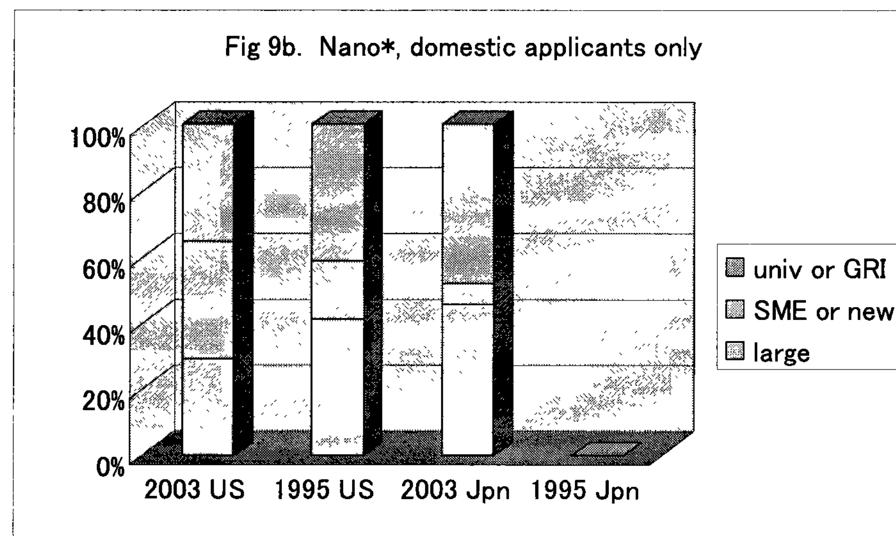


Fig 9b. Nano*, domestic applicants only
100%
80%
60%
40%
20%
0%
2003 US
1995 US
2003 Jpn
1995 Jpn
univ or GRI
SME or new
large

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[1] E.g., Rowan and Toyoda (2002), Ibata-Arens (2000), Nakagawa (1999), Suzuki (1999), Sakai (1990),.
[2] Kneller, RW. University-industry cooperation and technology transfer in Japan compared with the US: another reason for Japan's economic malaise? *University of Pennsylvania Journal of International Economic Law* Vol. 24(2) pp 329-449 (summer 2003).
[3] Kneller, RW. Autarkic drug discovery in Japanese pharmaceutical companies:
insights into national differences in industrial innovation. Research Policy Vol. 32 (10) (December 2003).
[4] SME White Paper 2003 and White Paper on European SME Enterprises, 5th Report 1997.
[5] The application (filing) fee to apply for a patent in either the USPTO or JPO is usually less than 1000 USD. But to engage patent attorneys to carefully draft the application and to deal with the sometimes long examination process at either the USPTO or JPO usually costs about 10,000 USD for a patent to be granted to a domestic applicant. If the applicant also applies for patents in foreign countries, costs increase greatly, especially if translation is required. When I worked in technology transfer at the US National Institutes of Health in the 1990s, we calculated that to obtain patents in the US, Japan and most major European countries for a single biomedical invention costs about 100,000 USD. Japanese patent applicants probably face even higher international costs because of higher translation costs in Europe as well as the US.
[6] Analysis of citations by US or Japanese patents to earlier patents or academic papers has been done – the number of citations not only suggesting the importance of a particular patent or academic paper but also the extent to which innovation in a particular industry relies upon academic research or previous inventions. Such analysis of US patents has shown that citations to academic publications are far more numerous in bio-medical patents, followed by patents in communications technology – suggesting that in these two industries academic discoveries are relatively more important for innovation than in other industries [Branstetter (2003)]. Similar analysis of Japanese patents has shown that citations to academic papers are also most common in biomedical patents, followed by nanotechnology patents [Tamada (2003)]. However, to my knowledge, these citation studies have not distinguished between old and new (or large and small) companies either as patent applicants or as holders of cited patents.
[7] Even a 12% share for Japanese venture companies is extremely surprising, since, until the late 1990s there was probably only one independent Japanese bioventure company (Medical Biological Laboratories in Nagoya), and its focus is designer antibodies, not genes and proteins per se. I am trying to clarify whether the 12% value includes foreign as well as Japanese applications, or whether some of the venture companies formed in the late1990s might have filed a large number of genomic patents. The most likely candidate would be Dragon Genomics, a spin-off from Takara Shusho, whose business plan, like Celera's, was focused on sequencing and identifying many genes and gene fragments.
[8] One exception is another 2002 JPO report (2002) that breaks down Japanese patent applications in the field of remote controlled nano imaging devices according to large company (89% of applications), venture company (1%), GRI (5%), mixed university and company inventors (4%), university faculty filing on their own (1%) and universities (0.3%).
[9] Kortum and Lerner (1998).
[10] The IPC codes are 8 character alpha-numeric codes published by the World Intellectual Property Organization. They tend to be based largely upon constituent materials or components, or underlying scientific processes, rather than upon end function. Therefore, for this analysis, they are not ideal. But because US, Japanese and most European patents are classified according to IPC codes, they can be used to compare patenting activity between countries. The

USPTO has its own unique classification system that is based more upon the end use or overall function of an invention. US patents thus have a dual classification, but the US classification cannot be used for international comparisons.

[11] When a company employee, GRI scientist, or faculty member in a US university makes an invention, the inventor is required to report the invention to his employer. The employer then decides whether it will require the inventor to assign the invention to the employer and then apply for a patent. This right of an employer to assert ownership over its employees' inventions is a standard element of most employment contracts. Many employers demand prospective assignment of any inventions their employees make. First assignees are listed on the front page of Japanese and US patents, and since first assignees are usually the inventors' employers, this usually indicates where the inventions occurred.

As discussed in a following paper, the case of Japanese university inventions was an exception. Until April 2004, faculty in most Japanese universities were able to retain ownership over most of their inventions. However they would more often assign their inventions to companies that helped fund their research than patent them themselves. Thus, probably a small proportion of inventions assigned to companies were actually invented in Japanese universities.

[12] In fact, most of these patents are from two GRIs, the Institute for Chemistry and Physics (Riken) and the Agency for Industrial Science and Technology (AIST). Both are semi-autonomous corporations, Riken under the Ministry of Education, Culture, Sports, Science and Technology (officially abbreviated as MEXT), and AIST under the Ministry of Economy Trade and Industry (METI). As I will describe in a following paper, it is not surprising that Riken and AIST are the two leading patent holders among public research institutions.

[13] SME White Paper FY 2003.

[14] Whittaker 1997.

[15] Sakai 1990

[16] Ibata-Arens 2000

Appropriability and the timing of innovation: Evidence from MIT inventions[1]

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April 2003

JEL Classification: L00, D21, D23, O31, O32, O34
Keywords: Appropriability, Patents, Innovation, Discrete Hazard Models

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[2]Thursby gratefully acknowledges support from the National Science Foundation (Awards SES-0094573 and NSF-IGERT 0221600). Both Thursby and Dechenaux thank the Alan and Mildred Peterson Foundation for research support.

Abstract

At least since Arrow (1962), economists have believed that strong property rights are necessary for firms to invest in innovation. This belief was a key principle underlying the Bayh-Dole Act, which gave universities the right to own and license federally funded inventions, because the commercialization of university inventions requires private firm investment in development, given the early stage of these inventions at the time that they are licensed. However, surprisingly little research has examined this key principle. In this paper, we exploit a database of 805 attempts by private firms to commercialize inventions licensed exclusively from MIT between 1980 and 1996 to address this issue. The data allow us to examine the timing of subsequent commercialization or termination of the licenses to these inventions as a function of the length of patent protection, as well as other measures of appropriability. We model the firm's investment decision as an optimal stopping problem, and we characterize the hazard rates of first sale and termination over time. In both the theory and the empirical analysis, we find two opposing effects of time. The length of patent protection provides an incentive for the firm to invest that declines with time; while the probability of technical success increases in each period that the firm invests. Competing risks models to predict the resulting hazards of first sale and termination reveal that, for these data, the hazard of first sale has an inverted u-shape and the hazard of termination has a u-shape. We find that increased appropriability, as measured by Lerner's index of patent scope and effectiveness of patents in a line of business, decrease the hazard of termination and increase the hazard of first sale.

1 Introduction

University patent licensing has grown steadily in the two decades since the Bayh-Dole Act gave universities the right to own and license the results of federally funded research.[3] While many researchers and policy makers cite the passage of the Bayh-Dole Act as instrumental in facilitating the commercialization of university inventions, others question whether the Act has mattered at all. As a result, the debate over the value of giving universities the property rights to federally-funded inventions has continued since the initial discussion of the Act in the late 1970s and shows no sign of abating. In fact, within the last year, Congress, the National Academies' Committee on Science, Technology, and Economic Policy, and the President's Commission on Science and Technology have all undertaken review of Bayh-Dole.

Beneath the rhetoric, there has been surprisingly little analysis of the key principle underlying the debate: would private firms adopt and commercialize university inventions in the absence of strong property rights to the inventions results? Some observers say the answer is yes. As noted by Nelson (2001), two of the most important university patents (Cohen-Boyer at Stanford and Axel at Columbia) were adopted by companies without exclusive licenses. In their case-study analysis, Colyvas et al. (2002) find that inventions "ready for use" (four of their ten cases) were successfully licensed and put to commercial use without exclusive license. There is also extensive evidence of university research that has been transferred to industry by other means than technology licensing, including publications, consulting, and conference participation (See, for example, Adams, 1990; Agrawal and Henderson, 2002; Cohen et al., 1998; Jaffe, 1989; Mansfield, 1995; and Zucker et al., 1998).

Nonetheless, the proponents of Bayh-Dole argue that because the commercial success of university inventions is highly uncertain and typically requires substantial development, private firms will not make the necessary investment unless they can appropriate the returns to that investment. It has long been recognized that

[3] According to the Association of University Technology Managers (AUTM), the number of universities with technology transfer offices grew from 20 in 1980 to over 200 in 1990. For the 95 US institutions responding to the AUTM survey in both 1991 and 1999, the number of inventions disclosed by faculty increased 65% to a total of 8457 in 1997, the number of new patent applications filed increased 175% to 4032, the number of license and option agreements executed increased 135% to 2734, and royalties increased more than 250% (in real terms) to around $665 million.

uncertainty and inappropriability can lead to underinvestment in research and development (the classic reference being Arrow, 1962). University inventions are uncertain and require subsequent development to achieve commercial success. A recent survey of businesses who license from universities indicates that almost half of university inventions fail (Thursby and Thursby, 2003). Moreover, a survey of sixty-two U.S. university technology transfer offices provides evidence that eighty-eight percent of the inventions licensed require further development, and seventy-five percent are so embryonic that commercial success requires faculty participation in the process (Thursby et al., 2001). Jensen and Thursby (2001) construct a model of exclusive licensing and show that the necessary faculty participation would not be forthcoming without license payments tied to firm performance, such as royalties or equity. The focus of this work, however, is the role of contracts in obtaining faculty cooperation rather than the role of appropriability.

In this paper, we exploit a unique database that allows us to address directly the issue of whether private firms would adopt and commercialize university inventions in the absence of strong property rights to the technology. We examine the population of 805 attempts by private sector firms to commercialize inventions assigned to the Massachusetts Institute of Technology and licensed exclusively by the institution between 1980 and 1996. We use information obtained from the MIT technology licensing office on the dates of patent award and license execution, as well as the timing of subsequent commercialization of those inventions or termination of the licenses. We examine the relationship between the length of patent protection remaining on the inventions as well as other measures of appropriability and commercialization efforts. We argue that the length of patent protection remaining on an invention provides an incentive for private firms to commercialize university inventions. However, given the early stage of most university technologies, their commercialization takes time, initially increasing the probability of commercialization and decreasing the probability of termination because the probability that development will yield a commercially viable product increases over time. We also argue that other measures of appropriability, such as patent effectiveness and patent scope, increase the hazard of first sale and decrease the hazard of termination.

In Sections 2 and 3, we present a model of exclusive licensing in which a single firm that has licensed a university invention decides in each period whether to invest in further development, thereby increasing the probability of (technical) success, or to terminate the project. If the firm is successful at commercialization, it earns monopoly profit until the patent expires. If successful, the firm sells its new product immediately. Because of the opposing effects of length of remaining patent protection and effect of time on the probability of technical success, we find that patent age may have non-monotonic effects on both the hazard of termination and the hazard of first sale. The model predicts that for inventions with a sufficiently low initial probability of technical success, the hazard of termination has a u-shape and the hazard of first sale has an inverted u-shape, a pattern that we find in our data. The model also supports the view that wider patent scope and more effective patents decrease (increase) the hazard of termination (commercialization) regardless of patent age.

In sections 4 and 5, we present the data and empirical results for competing risks regression models to predict the hazard of first sale and license termination for 805 attempts to commercialize MIT-assigned patents licensed exclusively between 1980 and 1996. We find strong support for a u-shaped relationship with the age of the patent and the hazard of termination and somewhat weaker support for an inverted u-shaped relationship between the hazard of first sale and patent age. We also find that several other measures of appropriability, most notably the effectiveness of patents in a line of business and Lerner's index of patent scope, increase the hazard of first sale and decrease the hazard of termination. Our results are robust to controlling for the general technical field in which the invention is found, and the source of funding for the invention.

These results contribute, not only to the growing literature on innovation based on university research, but also to the broader literature on the relation between patents and innovation. As emphasized in a recent survey by Gallini (2002), the link between patent strength and innovation is, in general, ambiguous. Models which examine the relation between R&D spending and patent length in the presence of uncertainty find they are positively related (see Kamien and Schwartz, 1974 and Goel, 1996). However, Horowitz and Lai (1996) find an inverse u-shape relationship between patent length and the rate of innovation, and Lerner (2002) finds empirical support for such a relationship. In this work, the negative effect of patent length on innovation comes from taking into account the cumulative process of innovation and strategic effects from subsequent research.[4] Our results differ in that we explicitly incorporate the uncertainty associated with development of university inventions and we abstract from strategic issues.

Finally, we contribute to the empirical literature on the effectiveness of patents in appropriating returns from R&D. Much of this work focuses on the effectiveness of patents relative to other mechanisms and differences in appropriability across industries and countries (see, for example, Levin et al., 1987, Cohen et al., 1998, and Cohen et al., 2000, Lanjoux and Cockburn, 2000). While a few studies examine whether products or processes would not have been developed in the absence of patents (Taylor and Silberston, 1973, Mansfield, 1986, and Mansfield et al., 1981), their evidence is based on perceptions of R&D personnel responding to surveys. To our knowledge, ours is the only study to directly examine the relationship between patent characteristics and commercialization or termination of projects.

2 The Model

In this section, we consider the problem faced by a firm that has licensed a university invention which requires further development before it can be successfully commercialized. We assume that the firm has an exclusive license agreement with the university so that if development is successful, it will earn monopoly profits per period until the patent expires, which occurs at $L \geq 2$.[5] The age of the patent at the time of license is given by a, $a \in \{0, \ldots, L\}$, and licensing periods are indexed by t, where $t \in \{0, \ldots, L-a\}$, so that $a+t$ represents patent age in period t of the license.

To successfully commercialize the invention, the firm must invest c per period. This running development cost includes not only internal costs but also payments to the university, such as milestones, minimum royalties, and sponsored research. The returns to this investment are uncertain for both technical and market reasons. In a recent survey of businesses that license-in university inventions, Thursby and Thursby (2003) found that 46% of all inventions licensed fail and of these 47% failed

[4]Kamien and Schwartz (1974) find a negative relation between rivalry and the magnitude of innovation.

[5]As a matter of fact, $L = 17$.

for purely technical reasons. This is not surprising since roughly half of university inventions licensed are no more than a proof of concept at the time of license (Thursby et al., 2001). Moreover, defining market opportunities for early stage inventions is highly uncertain, so much so that many university inventions end up with applications that were not even anticipated at the time of license (Shane, 2000, and Thursby and Thursby, 2002).

We denote the probability the firm's development effort is successful by $p_t \in [0, 1)$ $\forall t$.[6] This function represents the technical probability of success. While investment may not increase the probability of success in any period, it is natural to assume that p_t is non-decreasing. The firm would not invest unless this were the case.[7] We further assume, as we believe is intuitive, that for any sequence of probabilities of success $\{p_n\}_{n=0}^{L}$, the probability of of success grows at a finite rate, that is, $\frac{p_{n+1}}{p_n}$ is finite for every n.[8]

Suppose the firm is successful in period t, then expected cumulative discounted profit is given by $\tilde{\Pi}_{a+t}(\delta)$ where δ is the discount factor ($\delta = (1+r)^{-1}$ and $r > 0$ is the interest rate). Thus, from the firm's perspective, in any period before t, $\tilde{\Pi}_{a+t}(\delta)$ is a random variable with cumulative distribution function F_{a+t} on the interval $[0, \overline{\Pi}]$. We assume that the set of possible profit realizations is identical for all patent ages, but high realizations are more likely the younger the patent.[9] Formally, $F_n(B) \leq F_{n+1}(B), \forall n$. The distribution of profit outcomes when the patent is n years old first-order stochastically dominates the distribution of profit outcomes when the patent is $n+1$ years old. This reflects two aspects of the patent aging: first, the number of periods the firm can earn monopoly profit declines, and second, the probability that a competing firm will commercialize a non-infringing substitute

[6]This is an important difference between our model and that of Horowitz and Lai (1996) who consider innovations that are a sure success.

[7]Thus we assume p_t is the true probability of success. An alternative, and more complicated model, would allow the firm's perceived probability of success to differ from the true probability. In that case, investment could yield positive or negative observations which would be used to update the firm's perceived (prior) probability according to Bayes Rule.

[8]This rules out the probability of success jumping from an amount arbitrarily close zero to a non-zero amount. We assume that is p_t is close to zero, then so is p_{t+1}.

[9]It is not excluded that some of the outcomes in the interval will occur with zero-probability for some patent ages. We are thinking particularly about low (high) outcomes for low (high) patent ages.

increases (thereby reducing monopoly profit). Define $\mu_n \equiv E_n[\tilde{\Pi}_n]$, where E_n is the expectation operator. The subscript n indicates that the expected value is computed using F_n. We denote the sequence of expected profits, $\{\mu_n\}_{n=0}^{n=L}$, by $\mathcal{P}$. Given our assumption on the distribution function, μ_n is non-increasing in patent age.

If the firm is successful, it sells immediately. There are several reasons for this assumption. One is that it greatly simplifies the problem. In the Appendix we show how the firm's problem changes if it can delay selling. Second, and more importantly, the overwhelming majority of university licenses (and almost all of the MIT licenses) include minimum royalties or milestone payments designed to prevent licensees from delaying commercialization (Thursby et al., 2001). These payments, which we denote by $m \leq c$, reflect university attempts to ensure that the federal government does not "march-in" and exercise its right to find alternative licensees if it deems that the licensing firm "has not taken, or is not expected to take within a reasonable time, effective steps to achieve practical application of the subject invention."[10] In the context of our model, the assumption that $F_n(B) = 0$ for every $B \leq \delta\mu_{n+1} - m$ guarantees that the firm has no incentive to delay commercialization.

The firm's problem, then, is an optimal stopping problem similar to that analyzed by Roberts and Weitzman (1981).[11] Simply put, the firm's optimal decision rule is to continue in any period with a positive continuation value and stop as soon as the continuation value becomes zero. Using dynamic programming, the value of continuing at any t if the firm started to license when the patent was a years old can

[10]See Section 203 of the Bayh Dole Act. If the terms of the contract perfectly enforce "commercialization" one would expect march-in rights not to be exercised, and in fact they have not. In the public policy debates over Bayh Dole revision, Rai and Eisenberg (2002), argue that the march-in provisions should be strengthened.

[11]Our model is similar to their sequential decision process (SDP), although in their model, the SDP must go through a deterministic number of stages before completion. In our model, in every period, there is a positive probability that the current period is the period of completion. In this sense, our model bears many similarities to Grossman and Shapiro (1986), but their focus is on optimal development expenditure, rather than optimal stopping. They assume the value of investing is positive throughout so that termination is not an issue. Kamien and Schwartz (1971) examine similar problems under various assumptions about the probability of success. Optimal stopping problems have also been examined in the context of search (see Lippman and McCall (1976)) and diffusion of innovation (see Jensen, 1981; 2003).

be written as:

$$V_c(t, \Pi_{a+t}; a) = \max\{p_t \Pi_{a+t} + (1-p_t)\delta E V_c(t+1, \tilde{\Pi}_{a+t+1}; a) - c, 0\}, \tag{1}$$

where Π_{a+t} is the realized value of profit in period t. The expectation is taken over $\tilde{\Pi}_{a+t+1}$ and a is treated as a parameter. The terminal condition that ensures that the dynamic programming problem is well-defined is $\Pi_{L+1} \equiv 0$. When the patent expires, cumulative profits fall to zero with probability one. Given that success did not occur in $t-1$, (1) says that the value of continuing is equal to the maximum of 0, in which case the firm terminates the license, and profit if success occurs plus the value of continuing in the next period if development is unsuccessful, minus the development cost paid in the current period. We assume that $EV_c(0, \tilde{\Pi}_0; 0) > 0$ to ensure that the invention has a positive discounted expected value overall.

The optimal termination rule is simple: "*Continue to invest as long as $V_c > 0$. As soon as V_c drops to zero, terminate the license.*" Therefore the probability of termination conditional on neither termination, nor first sale, occurring before t is given by $p_f(t; a) = \Pr(V_c(t, \Pi_{a+t}; a) \leq 0) = F_{a+t}(B(t; a))$, where:

$$B(t; a) = \frac{c - (1-p_t)\delta E V_c(t+1, \tilde{\Pi}_{a+t+1}; a)}{p_t}. \tag{2}$$

$B(t; a)$ measures the net expected cost of continuing at period t, that is the development cost net of the discounted expected value of continuing in the next period, discounted by the probability of success in the current period.[12]

From $V_c(L+1-a; a) \equiv 0$, it follows that the firm terminates with probability one at $L+1$. Using this fact, the optimal stopping rule and first sale decision generate a well-defined probability distribution over termination dates in $\{0, \ldots, L+1-a\}$:

$$P_f(t; a) = p_f(t; a) \prod_{k=0}^{t-1} (1-p_k)(1-p_f(k; a)). \tag{3}$$

Similarly, the optimal first sale decision generates a well-defined probability distribution over dates of first sale in $\{0, \ldots, L+1-a\}$:[13]

$$P_s(t; a) = p_s(t; a) \prod_{k=0}^{t-1} (1-p_k)(1-p_f(k; a)). \tag{4}$$

[12]We suppress $\tilde{\Pi}_{a+t1}$ as an argument from $B(t; a)$ and the hazard functions defined below for notational convenience.

[13]$P_i(t; a) \leq 1$ for very t and $\sum_{t=0}^{L-a+1} P_i(t; a) = 1$, $i = f, s$.

The joint survival function in period t is the probability that the firm has neither terminated, nor commercialized in any period $k \in \{0, \ldots, t-1\}$. In the context of our model, it is given by:

$$s(t;a) = \prod_{k=0}^{t-1}(1-p_k)(1-p_f(k;a)) = \prod_{k=0}^{t-1}(1-p_k)(1-F_{a+t}(B(k;a))).$$

The hazard of termination in period t is the probability that the firm terminates in period t given that it neither terminated, nor commercialized before t and is given by:

$$h_f(t;a) \equiv \frac{P_f(t;a)}{s(t;a)} = p_f(t;a) = F_{a+t}(B(t;a)). \tag{5}$$

Similarly, the hazard of first sale t is given by:

$$h_s(t;a) \equiv \frac{P_s(t;a)}{s(t;a)} = p_s(t;a) = (1-p_f(t;a))p_t. \tag{6}$$

(6) represents the probability that the firm commercializes in period t conditional on the firm not having commercialized or terminated before t. It is straightforward to see that both hazard rates may decrease or increase as a patent ages. *Ceteris paribus*, an increase in a increases both the hazard of termination and the hazard of first sale because it increases the net expected cost of continuing given by (2). The question of interest, however, is how the hazard rates change over time given a.

3 Comparative statics

Comparative statics allow us to examine the effect of patent age, expected profit, and the probability of technical success on the firm's decisions. Not surprisingly, parameters that increase expected cumulative profits (such as patent scope and strength) decrease the hazard of termination regardless of patent age. Conversely, parameters that decrease expected profits (such as financial constraints) increase the hazard of termination regardless of patent age. The relation between patent age and termination is, as expected, more complex. The fact that an older patent provides exclusive legal rights for fewer periods provides an incentive for the firm to terminate sooner than if it held a more recent patent. However, the firm is more likely to be successful at development the longer it has invested, so that the effect of patent age $(a+t)$ on the hazard of termination may be non-monotonic. Finally, we show that the hazards of termination and first sale can be inversely related.

3.1 Termination decision

Consider, first, the effect of a more favorable distribution of profit outcomes on the hazard of termination. Proposition 1 below says that for two distributions of profit outcomes associated with an invention, the hazard of termination is lower in every period for the distribution with better outcomes than for the other distribution.

Proposition 1 *Given a and δ, if $\{F'_n\}_{n=0}^{L}$ and $\{F_n\}_{n=0}^{L}$ are such that for every n, $F'_n(B) \leq F_n(B), \forall X$, the hazard of termination is lower if the sequence of profit distributions is given by $\{F'_n\}_{n=0}^{L}$ than if it is given by $\{F_n\}_{n=0}^{L}$.*

Thus anything that improves the distribution of profits, such as wider patent scope or greater strength, will provide higher continuation values on average in every period of development and, therefore, a later termination date with lower probability of occurrence.

Ceteris paribus, factors that increase the firm's ability to appropriate returns from investment in the invention will have a positive effect on continuation independent of patent age. It is important to note, however, that patent characteristics associated with expected profits may have ambiguous effects on continuation. For example, inventions with fewer citations to prior art are more novel and may command higher monopoly profit, but their development is more uncertain. Assuming that less prior art increases the sequence of expected profit, $\mathcal{P}$, and decreases the probability of success in the first licensing period (p_0), the effect on the hazard of termination is ambiguous.

The same observation can be made regarding comparative statics on invention characteristics, such as whether the invention radically improves upon existing products or processes. Radical inventions are typically more difficult to develop, but yield higher monopoly profit if successful. In the model, more difficult development can be represented by a higher c, holding the sequence $\{p_n\}_{n=0}^{n=L}$ constant, which would increase the hazard of termination. On the other hand, higher profitability may counterbalance or overturn the effect of higher development costs. Therefore, it is not clear whether higher radicality should increase or decrease the hazard of termination.

In Proposition 2, we consider the effect of the discount factor δ. The traditional interpretation for δ is that it measures the interest forgone by investing in the project for one more period. Alternatively, we can view δ as a measure of the interest rate paid by the firm on loans associated with the investment, with a lower δ representing a higher interest rate. Proposition 2 follows from taking the view that δ represents the importance of financial constraints faced by the firm:

Proposition 2 *Given a, firms that face looser financial constraints have lower hazards of termination.*

Proof. See Appendix.

Finally, we consider the effect of patent age on the firm's decision to terminate the license in a particular period. Holding t constant, simple comparative statics show that $\frac{\partial B(t;a)}{\partial a} \geq 0$. Therefore, in any given period, a license executed for an older patent will have a higher probability of termination and thus, a higher hazard of termination. However, time may have a positive effect on the continuation value through increased development effort, or a higher probability of success.

Proposition 3 *Given the parameters of the model, if the distribution of profit outcomes changes slowly with patent age and the probability of technical success is low and increases slowly initially, then the hazard of termination decreases with patent age if the patent is young. Otherwise, the hazard of termination increases with patent age.*

Proof. See Appendix.

Patent age has an ambiguous effect on the hazard of termination because of the two opposing dimensions of time. As time passes, the chances that the firm's investment will yield a highly profitable product decrease (F_{a+t}) as the periods remaining on the patent decrease (and therefore the length of time it can earn monopoly profit), but the probability that the invention will lead to a product increases (p_t). In order for the hazard of termination to decrease over time, it must be the case that the positive effect of the increasing probability of technical success over time outweighs the negative effect of the distribution of profit outcomes over time. This suggests that if the hazard of termination ever decreases with patent age, then it must be for low patent ages, when the firm still expects relatively high cumulative profits, and the invention is at an early stage of development.

3.2 Commercialization decision

Recall from Section 2 that termination and the date of first sale are closely related. More precisely, the hazard of first sale increases if the hazard of termination decreases. Therefore, an increase in expected profit throughout the life of the patent decreases the hazard of termination, and thus increases the hazard of first sale, for every patent age.

Proposition 4 *Given a and δ, if $\{F'_n\}_{n=0}^{L}$ and $\{F_n\}_{n=0}^{L}$ are such that for every n, $F'_n(B) \leq F_n(B), \forall X$, the hazard of first sale is higher if the sequence of profit distributions is given by $\{F'_n\}_{n=0}^{L}$ than if it is given by $\{F_n\}_{n=0}^{L}$.*

To the extent that wider patent scope or strength increase expected profits, it follows that they increase the hazard of first sale for every patent age.

The hazard of first sale therefore increases whenever the probability of first sale increases. It decreases, however, only if the probability of first sale decreases enough. In a given development period, older patents represented by a higher a have a lower hazard of first sale simply because the probability that the license has not been terminated before reaching this development period is lower. The effect of development for a given age at the time of the license is ambiguous. We have the following proposition:

Proposition 5 *Given the parameters of the model, if the hazard of termination decreases with patent age, then the hazard of first sale increases with patent age. If the hazard of termination increases with patent age, the hazard of first sale could still increase if the probability of technical success increases sufficiently fast.*

Proof. See Appendix.

Note that even if the hazard of termination increases with patent age, this is not sufficient for the hazard of first sale to decrease for all patent ages.

In summary, the model implies a strong relationship between the hazards of termination and first sale because of the timing of decisions. We find that better appropriability in the sense of wider patent scope or more effective patents increases both the hazard of termination and the hazard of first sale. On the other hand, better appropriabiltity as measured by the age of the patent can have non-monotonic effects on both hazard functions. This ambiguity comes from the opposing effects of continued investment on the technical probability of success (a positive effect) and the decrease in the number of periods left on the patent (a negative effect). The shape of the hazard functions over time is therefore an empirical issue. Recall, however, that our assumptions on the probability of technical success are based on empirical evidence on the embryonic nature and high failure rate of university inventions. If we were to assume that the probability of success is initially close to zero, but increasing over time at a decreasing rate (i.e., diminishing returns to development), then one would expect the hazard of termination to decrease initially but eventually flatten out and perhaps increase.

4 Data

The data used to test the model's predictions were collected from the Technology Licensing Office (TLO) at the Massachusetts Institute of Technology on patents assigned to the Institute between 1980 and 1996 and subsequently licensed exclusively to private sector firms. The data include all patented inventions by MIT faculty, staff and students from 1980 through 1996 that were assigned to the Institute and licensed exclusively to at least one private firm.

Our data is an unbalanced, right censored panel. We have yearly data for each attempt from the date of the contractual agreement on the patent until one of the three events occurs: it is right censored (in 1996), it is terminated or it is commercialized. An observation begins the year that MIT TLO records indicate that a firm first licensed a patent. We code TERMINATION as zero, except in the year (if any) that MIT TLO records indicate that the licensing agreement by the given firm no longer covered the invention or if the patent expired, thereby negating the license. We code

FIRSTSALE as zero, except in the year (if any) that the MIT TLO records indicate that the first dollar of sales from a product or service embodying the invention was achieved.

Since our theoretical model provides hypotheses regarding the behavior of firms with exclusive licenses, we condition the empirical analysis on the TLO having licensed the invention exclusively. There are 805 exclusive attempts corresponding to 2845 periods in which licenses were at hazard.[14] While it is plausible that licenses are terminated after commercialization, the MIT licensing office reports that this is a rare event, and hence this information was not collected. That is, we only observe the first event that occurs. The analysis below predicts the likelihood of the first event.[15]

Table 1 reports the unconditional survival rates and the extent of right censoring for the sample of patents licensed exclusively. First and foremost, firms are far more likely to terminate licenses of patents than successfully commercialize them (288 terminations vs. 168 successes). The table also suggests that uncertainty associated with an innovation is generally resolved in the first 5 years of license. Note that from the 6th year on, the conditional probabilities are based upon small samples. 85% of licenses either lead to commercialization or are terminated by the end of period 5 and 90% of the observed events occur in the first five periods. We observe only 2 events after period 10. Figure 1 shows the reduced-form event hazards of termination and commercialization. The sparseness of this right tail implies that there is little information on which to estimate the baseline hazard. Therefore, we recoded all observations that survived more than five periods as right censored after five periods. Thus, in addition to the observations that are right-censored after 1996, we censored an additional 74 observations.

This does *not* mean that uncertainty is resolved within five years of issuance of a patent. As is evident in table 2, it is not uncommon for patents of medium age to be licensed, although this is very uncommon for old patents. It is not uncommon for licenses to survive well into patent life before first sale or termination (table 3).

[14] Although we leave their analysis for future work, there are only 163 non-exclusive licenses in the full sample. Very few patents are licensed exclusively in all fields of use and almost nothing is licensed non-exclusively. It is straightforward to define a field of use and the scope of a field is very flexible, so both sides are generally able to agree on a field of use in negotiation.

[15] Coding of commercialization was straightforward, as this is directly reported in the MIT data.

85% of licenses are resolved before patents reach age 11.

The variation in patent age at the time of license allows us to distinguish between the effects of the age of the license and the age of the patent on the hazards of first sale and termination. The former are measured in the baseline hazard estimates, while the latter are measured in the coefficients on age. This distinction is important because the age of the license captures the effects of firm learning. If the effects of patent age on first sale and termination are as predicted, this means that the effects exist even after the effects of firm learning about the commercialization of the technology have been controlled for.

Table 4 shows descriptive statistics for our analysis. We include several variables in our regressions. We measure AGE OF PATENT as the number of years since the patent was issued.

We employ several complementary measures to control for the quality of the patent. First, we use Lerner's (1994) measure of PATENT SCOPE, which is based upon the number of international patent classifications found on the patent. Lerner (1994) finds that this measure is associated with various measures of economic importance: firm valuation, likelihood of patent litigation, and citations. He argues that it represents broader scope of the monopoly rights covered by the patents. As implied by Propositions 1 and 4 respectively, PATENT SCOPE should be negatively related to the hazard of termination and positively related to the hazard of first sale.

Second, PRIOR ART CITED measures the number of prior patents cited by the focal patent. Out theory is ambiguous as to the expected signs of the coefficients on this variable. A decrease in prior art is associated with more novel and hence more risky knowledge, which should increase the hazard of termination. However, a decrease in prior art expands the scope of the property rights covered by the focal patent, which should decrease the hazard of termination, *ceteris paribus.*

Third, we employ 4 measures from the Yale survey on innovation (Levin et al., 1985; Levin et al., 1987). These measures are derived from managers opinions as to the effectiveness of different mechanisms used to appropriate the returns to innovation for process or product R&D in a line of business. The managers were asked to rate mechanisms on seven point Likert scales. The mechanisms are: patents prevent duplication; patents secure royalty income, secrecy, lead time, moving down the learning curve, and complementary sales and service efforts. We measure PATENT

STRENGTH as the average score for both patent measures for product and process innovations. As with PATENT SCOPE, PATENT STRENGTH should be negatively related to the hazard of termination and positively related to the hazard of termination. Using the Yale survey measures, we also examine the effects of SECRECY, LEAD TIME and moving down the LEARNING curve as the average score on each dimension for product and process innovations. We match the Yale survey line-of-business scores to patents by using the Yale survey concordance with SIC codes and the US Patent and Trademark Office's SIC-to-patent concordance.

We include several additional control variables in the hazard predictions. These variables are all designed to control for the commercial aspects of development. First, we include a dummy variable that takes the value one if the licensee is a STARTUP, which we define as a company not in existence prior to the licensing of the patent. STARTUP should influence the termination, which could occur if the company, rather than the technology failed. There is much additional risk associated with commercializing through a startup that is associated with setting up the new firm's infrastructure, and startups may also be liquidity-constrained relative to established firms. These factors suggest that new firms should discount the future heavily. Proposition 2 implies that these factors should increase the likelihood of termination. Recall from section 2 that this implies that the hazard of first sale should be decreasing in these factors.

Second, we control for the RADICALNESS of the invention. Following Shane (2001) and Rosenkopf and Nerkar (2001), we measure the RADICALNESS as a count of three-digit classes in which previous patents cited on the focal patent are found, but that the patent itself is not in. Following our discussion of proposition 1, we have no prior expectation of the relationship between RADICALNESS and the hazard of termination and commercialization. Radical technologies are more difficult to develop, but generate more profit if they are successfully developed.

Third, we include a dummy variable that takes the value one if the research that led to the invention was industry funded. Industry funded research is more likely to be directed, in the sense that firms are likely to expect tangible beneficial results from the research or the relationship with the investigator. Indeed, Goldfarb (2002) and Mansfield (1995) both find evidence consistent with the idea that the congruence of research goals is an important consideration in the research grant matching process.

We expect that INDUSTRY FUNDING should decrease the hazard of termination, and increase the hazard of first sale. Firms should be less likely to terminate efforts to commercialize inventions funded by themselves or competitor firms, as the results are likely to be more closely related to their strategic goals. Likewise, we should expect that industry funded research is more likely to result in a commercial product, as results stemming from such research would be more commercially relevant.

Fourth, we include a measure of a patent's GENERALITY following Hall, Jaffe and Tratjenberg (2001).

$$GENERALITY_i = 1 - \sum_{i}^{n_i} s_{ij}^2 \tag{7}$$

where s_{ij} is the percentage of citations received by patent i that belong to patent class j out of n_i patent classes. A high score suggests that a patent has been a component of inventions in many different patent classes, and hence more general. If more general technologies take longer to apply to particular applications, then we should expect the termination and commercialization decisions to be made more slowly for general inventions than for less general ones.

Finally we include TECHNOLOGY CLASS dummies. Following the Hall, Jaffe, and Trajtenberg classification of patents, we break the patents into five categories: drugs, electronics (including computers and communications), chemicals, mechanical, and other. We might expect drugs to take longer to reach first sale due to FDA regulations than, say, mechanical devices.[16]

5 Empirical Results

Our theory models the empirical reality in which attempts to commercialize patented inventions are either successful, in which case we observe a first sale, are terminated by either one of the parties of the license or by default if the patent expires, or are retained with neither event occurring. The appropriate empirical model for this is a competing risks model which must adjust for right censoring and the discrete nature

[16]Reduced form hazard ratios suggest that event patterns in the various categories are distinct. For example, licenses of drug patents tend to survive longer than other types of inventions. Unfortunately, the data do not allow us to econometrically distinguish these differences.

of the data. For detailed descriptions of competing risks models see Kalbfleisch and Prentice (1980) and Lancaster (1990). Let T_f be the duration of a patent that is licensed until first sale and T_d be the duration of a license until it is terminated. Define $T = \min(T_f, T_d)$ and let d_f be an indicator which equals 1 if a patent is commercialized (first sale) from a license and 0 otherwise. Let d_d be an indicator which equals 1 if a patent is terminated from a license and 0 otherwise. Only (T, d_f, d_d) are observed. Because d_f and d_d are observed exclusion restrictions are not necessary to uncover the latent survival functions, $S(k_f, k_d|x)$, if there is sufficient variation in the vector of regressors x (McCall 1993, Han and Hausman, 1990). Since our data are discrete, we employ a grouped data approach (Han and Hausman, 1990). Our model follows McCall (1996).

The probability of a patent being terminated from a license conditional on no events occurring through period $k-1$ is:

$$\Pr(T_d = k|X, T > k-1) = 1 - \exp(-\theta_d \exp(\alpha_{dk} + \beta_d' x)), \tag{8}$$

where x is a set of exogenous (possibly) time-varying regressors. Similarly,

$$\Pr(T_f = k|X, T > k-1) = 1 - \exp(-\theta_f \exp(\alpha_{fk} + \beta_f' x)), \tag{9}$$

is the probability a first sale associated with a patent occurs conditional on no events occurring through period $k-1$. (Period subscripts on x are dropped for readability.) Because the theory does not provide us with guidance as to possible exclusion restrictions, we assume that regressors x are identical in both equations.

The joint survivor function conditional on x is:

$$S(k_s, k_d|x) = \exp\left(-\theta_f \sum_{r=1}^{k_f} \exp(\alpha_{fk} + \beta_f' x) - \theta_d \sum_{r=1}^{k_d} \exp(\alpha_{dk} + \beta_d' x)\right). \tag{10}$$

In what follows let $\Theta = \{\theta_f, \theta_d\}$. α_{wk} are the baseline parameters and can be interpreted as:

$$\alpha_{wk} = \log\left(\int_{k-1}^{k} \lambda_w(t)dt\right),$$

where $\lambda_w(t)$ is the underlying baseline hazard function and $w \in \{f, d\}$. α_{dk} and α_{fk} are the respective baseline hazards and are assumed to follow a *2nd* order polynomial. A 2nd-order polynomial is sufficiently flexible to approximate a baseline hazard function of only five periods. Thus

$$\alpha_{wk} = \alpha_{0k} + \alpha_{1k}k + \alpha_{2k}k^2. \tag{11}$$

The vectors of parameters β_w represent the effects of the exogenous variables. Note that all covariates are constant except patent age, year and interaction terms of the controls with age. Define

$$\begin{aligned}
P_f(k) &= S(k-1,k-1|\Theta) - S(k,k-1|\Theta) - 0.5[S(k-1,k-1|\Theta) + S(k,k|\Theta) \\
&- S(k-1,k|\Theta) - S(k,k-1)|\Theta], \\
P_d(k) &= S(k-1,k-1|\Theta) - S(k-1,k|\Theta) - 0.5[S(k-1,k-1|\Theta) + S(k,k|\Theta) \\
&- S(k-1,k|\Theta) - S(k,k-1)|\Theta], \\
P_c(k) &= S(k-1,k-1|\Theta),
\end{aligned}$$

where $P_f(k)$ is the unconditional probability of first sale by the beginning of period k, $P_d(k)$ is the unconditional probability of a patent being terminated from a license by the beginning of period k, and $P_c(k)$ is the unconditional probability of neither event occurring through the beginning of period k. An adjustment, $0.5[S(k-1,k-1|\Theta) + S(k,k|\Theta) - S(k-1,k|\Theta) - S(k,k-1|\Theta)]$ is made because durations are measured in discrete time.

A key problem identified in the labor literature with competing risks models is that when the risks are not allowed to correlate, a potential bias may arise. Unobserved determinants of one event (first sale) may be correlated with unobserved determinants of the complementary event (termination) and duration (decision to do neither). We might expect unobserved components such as quality of the patent and uncertainty associated with success of the technology to affect both decisions. In our specification, the risks correlate by allowing a two mass-point distribution of location parameter pairs θ_{dj}, θ_{fj} where j=1,2. Each pair occurs with probability q_j. The four location parameters and one free probability are estimated by the data. Thus,

$$\wp_w(k) = \sum_{j=1}^{2} q_j P_w(k|\Theta_j) \tag{12}$$

The log-likelihood is:

$$\log\ L = \sum_{n=1}^{N}\sum_{k=1}^{K_n} d^n_{fk}\log\wp^n_{fk} + d^n_{dk}\log\wp^n_{dk} + (1-d^n_{fk})(1-d^n_{dk})\log\wp^n_{ck}. \tag{13}$$

for each of the K_n periods of each of the N attempts.

To identify the model, the baseline hazards α_{f0} and α_{d0} are fixed to zero. As there is no constant in the regression, we use deviations from the means in x.

We report the robustness of our results with respect to the different methodologies in table 5. The proportional hazards models reported in regressions a1 and a2 foreshadow the results of the more sophisticated competing risks models. In a1, an event is termination of a license, while in a2 an event is the first sale of a license. That is, the first model does not distinguish between right censoring and first sale, whereas the second model does not distinguish between right censoring and termination. Nevertheless, we find a u-shaped relationship between the patent age and the hazard of termination and more weakly find an inverse u-shaped relationship between patent age and first sale.[17]

In regression 5b we report the results of competing risks models with independent risks.[18] The coefficients on AGE and AGE^2 clearly depict a u-shape relationship between patent age and the hazard of termination that reaches its low point when patents are eight years from issuance. This relationship is robust to controlling for whether or not the firm was a START-UP, whether the research leading to the patent was funded by industry, the PATENT SCOPE, PRIOR ART CITED, the RADICALNESS and GENERALITY of the patent, potential macroeconomic effects (period dummies), the TECHNOLOGY CLASS dummies and the appropriability mechanisms that are effective in the line of business.

However, our results concerning the influence of PATENT AGE on the hazard of first sale do not show a curvilinear relationship between PATENT AGE and the hazard of first sale. In an unreported regression, we find that if we drop the quadratic term, the coefficient on patent age is positive and significant when risks are restricted to be independent.

In regression 5c we allow for correlated risks. We strongly reject the hypothesis that there is no unobserved heterogeneity (LR statistic = 63.24).[19] We continue to

[17]Note that whereas in the competing risks regressions we report estimated coefficients, in these two regressions we report the proportional change in hazard with a unit change in the independent variable.

[18]To map this regression onto the likelihood function, note that only one mass-point is allowed, i.e, one $\{\theta_d, \theta_f\}$ pair. That is, we restrict α_{12}, α_{22}, θ_{21}, θ_{22} and q_2 to 0.

[19]It is interesting to note that the unobserved components seem to be positively correlated. We

robustly find that the hazard of termination has a u-shape in patent age, although our standard errors are larger than in the restricted regressions. Similarly to regression 5b, we find evidence that the hazard of first sale has an inverted u-shape in patent age or is relatively flat, although here the signal is slightly stronger, as the z-statistic on the quadratic term moves from -1 to -1.4.

In table 6 we explore the sensitivity of the results to the inclusion of various controls. Regardless of the controls we add, we find a u-shaped relationship between PATENT AGE and the hazard of termination. We see little difference of the effect of PATENT AGE on the hazard of first sale when we add additional controls in regressions 6a and 6b as compared to regression 5c.

One possible explanation for the null results for commercialization and the significant results for termination is that they are artifacts of different commercialization horizons for different technologies. Therefore in regression 6c, we interact the TECHNOLOGY CLASS dummies with PATENT AGE. We find no statistically significant differences by technology in the effects of age on either commercialization or termination. Moreover the u-shaped relationship of PATENT AGE and termination is robust to the inclusion of these interaction terms. For commercialization, the inclusion of these interaction terms allows us to measure the effect of the inverse u-shaped relationship between PATENT AGE and commercialization with more precision. In regression 7c the linear term is significant and positive while the quadratic term is marginally significant and negative at the 90% level.

However, in the commercialization regression, we fail to reject the null hypothesis that each coefficient is zero when we add time-period controls in regression 6d. In particular, when we take into account whether the decision occurred between 1980-1984, 1985-1989 and 1990-1996, the z-statistics drop to about 1.4. Indeed, a likelihood ratio test fails to reject the hypothesis that the PATENT AGE and PATENT AGE^2 coefficients are jointly zero in this regression. The results for termination remain robust to the inclusion of period effects.

find this result weakly in all models we estimated with unobserved heterogeneity. Interpretation of this result depends on what we believe is unobserved. For example, if we are picking up unobserved quality, then we would think of θ_{11} and θ_{12} as picking up high-quality patents, and θ_{21} and θ_{22} as picking up low quality patents. In this case the model is predicting much lower hazards of events with high quality patents than low quality patents, and that 46% of the patents are high quality.

Table 7 provides a robustness check for the quadratic form of the relationship between age and termination, and age and first sale. When we remove the quadratic term from the first sale equation we do not find a monotonically increasing function, rather we find a zero coefficient on the linear patent age term (regression 7b). Nor do we find any evidence of a cubic relationship (regression 7a). Our data suggest that if there is a relationship between PATENT AGE and the hazard of first sale, a quadratic form fits the data best. However, the signal is weak and our data are too noisy to measure it convincingly.

In contrast, the hypothesis that the PATENT AGE and PATENT AGE^2 coefficients are jointly zero in the termination equation is rejected at the 95% level. In regression 7d we see that the relationship is clearly not linear. Interestingly, the cubic form seems to fit reasonably well in regression 7c. The shape of this cubic function predicts a modestly increasing function until a patent is three years of age followed by an inverted-u that reaches a minimum when at 11 years and increases through the age of 17. However, the null hypothesis that the cubic form does not explain the data any better data any better than the quadratic form cannot be rejected at the 90% level.

In addition, we measured the relationship using 14 age dummies for PATENT AGE and PATENT AGE^2. Applying all time constant controls, the data predict a u-shape for termination, and we generally measure zero coefficients for the hazard of first sale.[20]

In short, we are quite confident that there is a u-shaped relationship between a patent's age and the hazard of termination, whereas we find a relatively flat relationship between a patent's age and the hazard of first sale. We offer two explanations for this weak result for the first sale hazard. The first is that there is simply less information about commercialization in the data than termination. In table 1 we see that 18% (146 of 805) of the patents are commercialized by the fifth period. Second, the decision to sell is subject to more factors beyond the control of the decision makers than the decision to terminate. For example, an intent to commercialize can be confounded by such exogenous factors as the state of the underlying technology or market demand. As a result, it is likely more difficult to measure the factors

[20]This pattern becomes clear after smoothing with three-year moving averages. These regressions are available from the authors upon request.

that influence technology commercialization precisely than the factors that influence license termination.

We base our analysis of the magnitude of the effects on regression 5c. We report the mean predicted hazards of termination and first sale for all licenses at various simulated patent ages in period 2. The results for termination appear in figure 2. A 95% confidence interval is also depicted. As we can see, increasing the age by one year for a patent of mean age (5) increases the hazard probability of termination by 0.006 (since the mean predicted hazard of 5 year old patent is 0.06; this implies a 10% decrease in the predicted hazard). The effect begins to reverse itself as a patent reaches age 9. In Figure 3 we present the similar graph for the hazard of first sale. Here the hazard of first sale increases by 7% when patent age increases from age 5 to 6. The figures also depict 95% confidence intervals for these estimates. As expected, the intervals are at their narrowest points at the mean age of 5. Reflecting our general results, they are much narrower in figure 2 (termination).

Recall that propositions 1 and 4 give unambiguous implications for PATENT STRENGTH and PATENT SCOPE on the hazards of termination and first sale, respectively. Across all our regressions, we find a robust positive effect for the PATENT STRENGTH in a line of business on the likelihood of first sale and a robust negative effect on the likelihood of termination. Because these measures are derived from a Likert scale, we look at effect of a change in one standard deviation from the mean. If managers in a line of business rated the effectiveness of patents one standard deviation higher than the mean for all other lines of business, the hazard of termination decreased by 0.003 which is a 5% hazard change (this difference is significant at the 99% level). An increase in one standard deviation from the mean increases the hazard of first sale by 0.004 which is a 7% hazard change (this difference is significant at the 99% level). We also find a robust effect of PATENT SCOPE on first sale across all regressions, although we do not find such an effect on termination. With regards to patent scope, if each sample patent had spanned one additional category, then the mean increase of hazard of first sale would be 0.029 or 59% (difference significant at the 95% level). As anticipated by our discussion of comparative statics in Section 3, we find non-robust results for the effects of PRIOR ART CITED. Although not always measured precisely, patents that cite more prior art are more likely to be terminated.

Though speculative, we also find other interesting empirical results. As we would expect, licenses of innovations stemming from INDUSTRY-FUNDED research are less likely to be terminated. On average, the predicted decrease in hazard of termination of a license of a patent stemming from research funded by industry is 0.04 (difference significant at the 95% level). This reflects a 57% decrease in the predicted hazard. There is no consistently measurable effect on the hazard of first sale. This suggests that INDUSTRY-FUNDED inventions are valuable, but take longer to commercialize. We note that this result is consistent with firm's shelving industry funded inventions.

Our results concerning the licensing to a STARTUP and both commercialization and termination are intriguing. In table 6 we find that the hazard of termination *and* first sale decrease if the technology is licensed to a STARTUP. This result is sensitive to allowing for unobserved heterogeneity, whereas the first sale result is sensitive to the inclusion of time dummies. This result does not match the prediction of proposition 2 and is left for further study.

In some regressions we find that technologies that have broader applications are also more difficult to commercialize. However, the significance of this result is highly dependent on the specification. One might speculate that the nature of general technologies is such that they are farther from a commercial application. That is, less specialized technologies are less likely to be immediately useful.

Finally, technologies that are more radical are more likely to be commercialized. Again, this result is sensitive to specification, although it does not disappear with the inclusion of various controls (see regression 6d). Each additional three-digit class that previous patents cited on the focal patent increases the hazard of first sale by 0.004, which is 8%. This difference is significant at the 95% level. This result suggests that the increase profit potential of radical technologies overwhelms the increased risk associated with such technologies.

6 Conclusions

In this paper, we argue that keys to understanding much of the Bayh-Dole policy debate are none other than the problems of appropriability and uncertainty identified by Arrow (1962) nearly a half a century ago. To do so, we examine a model of exclusive licensing in which a single firm has licensed a university invention that requires further development in order to be successful commercially. Success is uncertain for both technical and market reasons. In each period, the firm decides whether to invest in further development, thereby increasing the probability of (technical) success, or to terminate the project. If the firm is successful at commercialization, it earns monopoly profit until the patent expires. We then characterize the hazard of termination and first sale as a function of the patent age, expected profit, and the probability of technical success. Parameters such as patent scope and strength which increase expected cumulative profits decrease the hazard of termination regardless of patent age. The relation between patent age and termination is, however, more complex. The fact that an older patent provides exclusive legal rights for fewer periods provides an incentive for the firm to terminate sooner than if it held a more recent patent. However, the probability the invention will succeed technically is higher the longer the firm has invested, so that the effect of patent age $(a+t)$ on the hazard of termination may be non-monotonic.

Our empirical results provide strong support for the view that the ability to appropriate returns is important for inventions whose success is highly uncertain. We find that increased appropriability, as measured by Lerner's index of patent scope and effectiveness of patents in a line of business, decrease the hazard of termination and increase the hazard of first sale. We find a u-shaped hazard of termination which is consistent with the opposing effects of time on the probability of success and appropriability as measured by the length of time left on the patent in the model. Our results on the hazard of first sale are less robust. The theory suggests that, if the firm sells as soon as the invention is successful technically, the hazards of termination and first sale will be inversely related. However, our empirical results show a flatter hazard of first sale.

Several caveats may explain the latter result. First, note that our characterization of the hazard of first sale and termination is based on the assumption that the firm introduces the invention to the market as soon as it is successful. If delaying first sale is profitable, the hazard for first sale and termination need not be inversely related, and in fact, we cannot characterize the relation. A variety of factors related to strategic or other aspects of the market could clearly make delaying first sale optimal. Second, both the theoretical and empirical analysis presume that firms licensing these inventions intend to commercialize them. While we believe this is a fair assumption given the march-in rights contained in the Bayh-Dole Act, it is possible that university attempts to prevent firms from shelving are not perfect. If milestones or annual fees are sufficiently low, it may be a profitable strategy for firms to maintain the license, preventing competitors from having access (as would be the case if the invention were returned to MIT). While we cannot eliminate this possibility nor identify when it might be happening, we suspect that our first caveat is more likely given the importance that technology transfer offices attach to due diligence in order to prevent shelving.[21]

Finally, note also that we have presumed that termination results when the firm decides not to continue developing a commercial product. However, if the property rights are weak, as we might expect in say, electronics or mechanical engineering inventions, a firm may maintain a license until critical, but non-protectable knowledge is transferred, and then drop the license and invent around the invention.[22] Hence, a result of a terminated patent (license) is not necessarily indicative of lack of technology transfer, or of a technology failure in general, except in the sense that the university, and perhaps inventor if a complementary consulting arrangement does not exist, will not receive rents (Henrekson and Goldfarb, 2002).[23]

These caveats aside, our results contribute to the growing literature on innovation based on university research. While much research has focused on spillovers through publications, consulting, and conference participation (see, for example, Adams, 1990; Agrawal and Henderson, 2002; Cohen et al., 1998; Jaffe, 1989; Mans-

[21]Recall that Thursby et al (2001) found this in their survey of 62 universities. In the particular case of MIT, several companies lost their licenses when they did not make annual payments or failed to meet a milestone. This is, of course, much more common with start-ups and small firms. In many cases, writing a business plan was a milestone and when the plan was not delivered, the firm would lose its license.

[22]Katharine Ku, head of the Stanford Office of Technology Licensing has indicated to the authors that not only does this happen, but it is considered fair-play and not at all unethical.

[23]Under the invent-around scenario the university may still receive rents if the license involved the transfer of equity to MIT. In this case returns are tied to profitability of the firm, rather than profitability of the specific licensed patent. Since equity is permanent, MIT could earn returns even if a particular invention were terminated. This may explain differential use of equity in licensing agreements across types of technology.

field, 1995; and Zucker et al., 1998), relatively little empirical research has explored the licensing mechanism, and in particular the question of whether private firms would adopt and commercialize university inventions in the absence of strong property rights to technology. Our results support the key principle underlying the Bayh-Dole Act. The ability to appropriate the returns to investment in innovation enhances the commercialization of technology licensed by universities to private firms.

Our results also contribute to the broader literature on the relationship between patents and innovation. Gallini's (2002) review indicates that the link between patent length and innovation is ambiguous, in general, but may have an inverted u-shape because of the incentives associated with entry. We contribute to this literature by showing that, even without sequential innovation, the combined effects of uncertainty and appropriability lead to an inverted u-shaped relationship between patent age and the hazard of first sale and a u-shaped relationship between patent age and the hazard of license termination.

Lastly, we contribute to the empirical literature on the effectiveness of patents in appropriating returns from R&D. In contrast to prior studies based on surveys of the perceptions of R&D personnel, we provide direct empirical evidence of the relationship between patent characteristics and commercialization of products or termination of projects.

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7 Appendix

7.1 Delaying first sale

To simplify notation, we let $m = 0$, in which case the license includes no financial incentives to prevent the firm from delaying first sale. If the firm is able to maintain its license without selling even after development has been successful, it compares the value of profits it can achieve by commercializing this period to the value it could achieve by delaying optimally. Since $\mu_{a+t+s} < \mu_{a+t+1}$, given the information available to the firm at period t, it does not anticipate delaying for more than one period. Therefore the value function writes:

$$V_c(t, \Pi_{a+t}; a) = \max\{p_t \max\{\Pi_{a+t}, \delta\mu_{a+t+1}\} + (1 - p_t)\delta EV_c(t + 1, \tilde{\Pi}_{a+t+1}; a) - c, 0\}. \tag{14}$$

Since $\mu_{a+t} > \delta\mu_{a+t+1}$, it is clear that $EV_c(t, \Pi_{a+t}; a)$ is unchanged as compared to the case where delaying is not possible.

Suppose $\Pi_{a+t} < \delta\mu_{a+t+1}$ so that the firm chooses to delay first sale, then (14) becomes:

$$V_c(t, \Pi_{a+t}; a) = \max\{p_t\delta\mu_{a+t+1} + (1 - p_t)\delta EV_c(t + 1, \tilde{\Pi}_{a+t+1}; a) - c, 0\}. \tag{15}$$

The ability to delay bounds the value of V_c below, and possibly, away from 0. If $V_c(t, \Pi_{a+t}; a) > 0$, then the firm continues. If not, the firm stops. Therefore, in any period t for which $V_c(t, \Pi_{a+t}; a)$ given by (15) is greater than zero, the firm will continue with probability 1. The reservation value that governs the optimal termination decision is below the reservation value that governs the optimal first sale decision. If $V_c(t, \Pi_{a+t}; a)$ given by (15) is less than zero, then the firm will never delay, and the value function is effectively given by (1). The reservation value that governs the optimal termination decision is higher than the reservation value that governs the optimal first sale decision.

If the firm succeeded at t, its dynamic programming problem reduces to choosing the optimal date of first sale according to the following value function:

$$V_s(t, \Pi_{a+t}; a) = \max\{\Pi_{a+t}, \delta\mu_{a+t+1}\}.$$

The terminal condition is given by $V_s(L + 1) \equiv 0$.

Suppose that there exists a set D of consecutive periods in which (15) is greater than zero. Then the probability that the firm will sell in some period $t \in D$ is:

$$\begin{aligned} q_s(t;a) &= [1 - F_{a+t}(\delta \mu_{a+t+1})][p_t \prod_{s=0}^{t-1}(1 - p_f(s;a))(1 - p_s) + \\ & \sum_{s=1}^{t-\min\{D\}} p_{t-s} \prod_{i=0}^{t-s-1}(1 - p_f(i;a))(1 - p_i) \prod_{i=1}^{s} F_{a+t-i}(\delta \mu_{a+t-i+1})]. \quad (16) \end{aligned}$$

The first bracketed term is the probability that the firm will not delay in period t. The first part of the second bracketed term the probability that the firm is successful in period t, and the second part is the probability that the firm was successful in a period of D different from t, but chose to delay. Thus, although we can compute the probability of first sale in a given period t, given that the firm could have optimally delayed sales in previous consecutive periods, characterizing the hazard of first sale is intractible.

7.2 Proof of Proposition 2

Given a, let $\hat{t}(a) < L - a$ be that period of time for which:

$$p_{\hat{t}(a)}\mu_{a+\hat{t}(a)} - c \geq 0 \text{ and } p_t \mu_{a+t} - c < 0, \forall t > \hat{t}(a).$$

Then, $EV_c(\hat{t}(a) + 1; a) = 0$. Using (1) and working backward from $L - a$, we obtain for $t < \hat{t}(a)$, and some realization of $\tilde{\Pi}_{a+t}$:

$$EV_c(t;a) = \max\{p_t \mu_{a+t} + \sum_{n=0}^{\hat{t}(a)-t-1} \delta^n \prod_{i=1}^{n}(1 - p_{t+i})(p_{t+n+1}\mu_{a+t+n+1} - c), 0\}. \quad (17)$$

Differentiating $B(t;a)$ given by (2) with respect to δ yields $\frac{\partial B(t;a)}{\partial \delta} \leq 0$. This implies that for a given patent age $a + t$, the probability of termination decreases with δ, which in turn implies that if $\delta' > \delta$, the hazard of termination at $a + t$ is lower at δ' than at δ.

7.3 Proof of Proposition 3

We wish to find conditions under which the hazard of termination decreases with patent age. A necessary condition for the hazard of termination to decrease with patent age is for a given a, $B(t+1;a) < B(t;a)$. A sufficient condition is that the distribution function does not change rapidly between $a+t$ and $a+t+1$. Since $\tilde{\Pi} \in [0,\overline{\Pi}]$, if $c \leq \delta(1-p)EV_c$, then $X \leq 0$, and thus $p_f = 0$. Therefore, in the analysis below, we assume that $\delta(1-p_t)EV_c(t+1;a) - c < 0$. Using (2), $B(t+1;a) < B(t;a)$ if and only if:

$$\frac{p_{t+1}}{p_t} \geq \frac{c - \delta(1-p_{t+1})EV_c(t+2;a)}{c - \delta(1-p_t)EV_c(t+1;a)}. \tag{18}$$

The left-hand side is strictly greater than 1, so the condition will definitely be satisfied if the right-hand side is less than or equal to 1. This is the case if and only if:

$$\frac{EV_c(t+2;a) - EV_c(t+1;a)}{p_t} \geq \frac{p_{t+1}}{p_t} EV_c(t+2;a) - EV_c(t+1;a) \tag{19}$$

Given $EV_c(t+2;a) - EV_c(t+1;a) > 0$, then if (19) is satisfied, it must be the case that $\frac{p_{t+1}}{p_t}$ and p_t are small enough. p_t cannot be too small (for example, p_t must be bounded away from 0). We need to find conditions under which $EV_c(t+2;a) - EV_c(t+1;a) > 0$. Suppose $EV_c(t+2;a) > 0$ and $EV_c(t+1;a) \geq 0$. Using (1), we have:

$$EV_c(t+2;a) - EV_c(t+1;a) = [1 - \delta(1-p_{t+1})]EV_c(t+2;a) - (p_{t+1}\mu_{a+t+1} - c), \tag{20}$$

If $p_{t+1}\mu_{a+t1} \leq c$, then (18) is definitely satisfied even if $EV_c(t+2;a) > 0$ is weakened to $V_c(t+2;a) \geq 0$ because from $p_{t+1}\mu_{a+t1} \leq c$, it follows that $EV_c(t+2;a) = 0 \Rightarrow EV_c(t+1;a) = 0$.

Since we clearly have:

$$\mu_{t+1} > \delta EV_c(t+2;a),$$

the right-hand side of (20) decreases with p_{t+1}, so that (20) will be satisfied if p_{t+1} is small enough and $EV_c(t+2;a)$ is large. This implies that a must be small. Therefore, if a is close to zero, for any two consecutive, periods t and $t+1$, such that $\frac{p_{t+1}}{p_t}$ is greater than, but close to 1, and p_t is small, the hazard of termination decreases with t. Otherwise, the hazard of termination increases with t.

7.4 Proof of Proposition 5

For a given t, the hazard of first sale clearly decreases with a since the hazard of termination increases with a. For a given a, a change in the hazard of first sale between t and $t+1$ is given by:

$$\Delta_s = (1 - p_f(a + t + 1))p_{t+1} - (1 - p_f(a + t))p_t.$$

If $p_f(a + t + 1) \leq p_f(a + t)$, then Δ_s is clearly positive. Δ_s is negative only if $p_f(a + t + 1)$ is sufficiently larger than $p_f(a + t)$. Therefore the relationship between p_f and Δ_s is generally ambiguous when p_f increases with t.

Table 1: Unconditional survival rates

Period	Abandon	First Sale	Right Censored	Surviving	Total
1	74	49	78	604	805
2	32	26	49	497	604
3	54	40	98	305	497
4	49	20	35	201	305
5	34	11	34	122	201
6	8	2	9	103	122
7	10	6	11	76	103
8	6	2	9	59	76
9	0	11	9	39	59
10	1	0	14	24	39
11	1	1	7	15	24
12			2	13	15
13			7	6	13
14			2	4	6
15			2	2	4
16			2	0	2
Totals	269	168	368	0	2875

Table 2: Age of patents at time of license

Age	Number	Percent	Cumulative Percentage
0	91	11.30	11.30
1	113	14.04	25.34
2	113	14.04	39.38
3	106	13.17	52.55
4	71	8.82	61.37
5	69	8.57	69.94
6	46	5.71	75.65
7	67	8.32	83.98
8	38	4.72	88.70
9	34	4.22	92.92
10	14	1.74	94.66
11	11	1.37	96.02
12	10	1.24	97.27
13	6	0.75	98.01
14	9	1.12	99.13
15	5	0.62	99.75
16	2	0.25	100.00
Total	**805**	**100.00**	

Table 3: Age of patents when events are observed

Patent Age	Termination	Commercialization	Right Censored	Total	Percent	Cumulative Percent
1	18	1	0	19	2.36%	2.36%
2	17	12	8	37	4.60%	6.96%
3	28	18	35	81	10.06%	17.02%
4	24	8	29	61	7.58%	24.60%
5	32	17	49	98	12.17%	36.77%
6	39	15	46	100	12.42%	49.19%
7	18	10	39	67	8.32%	57.52%
8	14	16	77	107	13.29%	70.81%
9	11	10	27	48	5.96%	76.77%
10	3	12	27	42	5.22%	81.99%
11	8	8	22	38	4.72%	86.71%
12	11	8	19	38	4.72%	91.43%
13	8	4	10	22	2.73%	94.16%
14	3	3	7	13	1.61%	95.78%
15	8	2	3	13	1.61%	97.39%
16	0	0	5	5	0.62%	98.01%
17	9	2	14	16	1.99%	100.00%
Total	**251**	**146**	**417**	**805**		

Table 4: Descriptive statistics

Variable	Mean	Std Dev	Min	Max
PATENT AGE	5.140	3.399	1	17
PATENT AGE^2	37.965	48.426	1	289
PATENT AGE^3	351.739	676.725	1	4913
Nature of Technology				
START-UP	0.327		0	1
PATENT SCOPE	1.339	0.639	1	6
PRIOR ART CITED	9.968	11.926	0	70
RADICALNESS	5.814	5.405	0	57
INDUSTRY FUNDED	0.168		0	1
GENERALITY	0.302	0.315	0	0.9
Technology classes				
DRUG PATENT	0.216		0	1
CHEMICAL PATENT	0.311		0	1
ELECTRIC PATENT	0.265		0	1
MECHANICAL PATENT	0.032		0	1
Appropriability Measures				
LEAD TIME	5.369	0.506	4	6.13
SECRECY	3.923	0.406	3	4.88
LEARNING	5.003	0.435	4	5.75
PATENT STRENGTH	4.108	0.747	1.75	5.32
Period Dummies				
YEAR 1980-1984	0.257		0	1
YEAR 1985-1989	0.314		0	1

Table 5: Results using different methodologies

NAME	Cox Proportional Hazards (a1) Termination Hazard Ratio	(a1) Termination Z-Stat	(a2) First Sale Hazard Ratio	(a2) First Sale Z-Stat	Competing Risks with Independent Risks (b) Termination Parameter	(b) Termination Z-Stat	(b) First Sale Parameter	(b) First Sale Z-Stat	Competing Risks with Unobserved Heterogeneity (c) Termination Parameter	(c) Termination Z-Stat	(c) First Sale Parameter	(c) First Sale Z-Stat
PATENT AGE	**0.769**	-3.990	**1.208**	2.180	**-0.300**	-3.661	0.156	1 476	**-0.271**	**-2.579**	0.194	1.460
PATENT AGE²	**1.013**	3.110	0.992	-1 380	**0.019**	4.030	-0.006	-0 983	**0.015**	**2.548**	-0.011	-1 401
Nature of Technology												
START-UP	1.230	1 510	1.101	0.530	0.048	0.282	0.193	0 957	**-1.197**	**-5.323**	-0.350	-1 311
PATENT SCOPE	0.943	-0.540	**1.345**	2.840	-0.092	-0.767	**0.277**	2.040	-0.079	-0.434	**0.492**	2.903
PRIOR ART CITED	1.002	0.180	0.982	-1.260	0.014	1.399	-0.017	-0.969	-0.015	-1.026	**-0.050**	-2.503
RADICALNESS	0 992	-0.450	1.021	0.820	-0.008	-0.507	0 026	0.959	0 028	0 994	**0.078**	2.342
INDUSTRY FUNDED	**0.658**	-2.080	1.069	0.290	-0.354	-1.578	-0 064	-0.232	**-0.609**	**-1.980**	-0.335	-0.952
GENERALITY	**1.881**	2.630	**0.427**	-2.900	0 029	0.105	**-0.642**	-2 192	-0.199	-0.530	-0.661	-1 613
Technology classes												
DRUG PATENT	0.867	-0.420	0.716	-0.740	-0.048	-0.117	-0.188	-0.337	0.097	0.139	-0.522	-0.725
CHEMICAL PATENT	1.091	0.360	**2.029**	2.120	0.158	0 602	0 676	1.943	0 149	0 407	0 299	0 692
ELECTRIC PATENT	0.826	-0.790	1.959	1.880	-0.166	-0.626	0.521	1.400	0 326	0.884	**1.465**	3 115
MECHANICAL PATENT	0.810	-0.480	0.832	-0.230	0.026	0.065	-0.112	-0.146	1.028	1.802	1.376	1 310
Appropriability Measures												
LEAD TIME	**2.389**	3.120	0.528	-1.850	**0.883**	3.331	-0.622	-1.606	0.161	0 435	**-1.136**	-2.141
SECRECY	**0.444**	-3.240	1.612	1.430	**-0.930**	-3.540	0.495	1 223	-0.856	**-2.272**	**1.082**	2.016
LEARNING	**0.461**	-2.560	**3.020**	2 580	**-0.723**	-2 380	**1.043**	2.099	0 053	0.127	**1.353**	2.113
PATENT STRENGTH	**0.589**	-3.250	**2.216**	3 030	**-0.710**	-3.805	**0.756**	2.388	-0.842	**-2.961**	**1.223**	3.108
Period Dummies												
YEAR 1980-1984	**0.276**	-2.160	1.662	1.210	0.061	0.231	-0.365	-1.640	0 415	1.120	-0.093	-0.330
YEAR 1985-1989	**0.630**	-2.440	1.393	1.590	**0.648**	3 397	**-1.147**	-4.307	0.503	1 850	**-1.781**	-5.577
α_{1l}					**-1.376**	-4.226	**-0.808**	-2.099	**-2.923**	**-3.590**	**-1.777**	-3.045
α_{2l}					**3.704**	5 712	**2.004**	2.770	**9.441**	**4.537**	**5.958**	4.482
θ_{1l}					**0.234**	2.871	**0.100**	2.334	0.002	1.521	0.001	1.220
θ_{2l}									1.087	1 474	0 305	1.816
q_l											**0.5430**	2 807
Failures	243		145		243		145		243		145	
# Licenses		805				805				805		
Time at risk (years)		2403				2403				2403		
Log Likelihood	-1459.19		-881.74			-1087.1454				-1055.5320		

Table 6: Competing risks model with unobserved heterogeneity

NAME	(a) Termination Parameter	(a) Termination Z-Stat	(a) First Sale Parameter	(a) First Sale Z-Stat	(b) Termination Parameter	(b) Termination Z-Stat	(b) First Sale Parameter	(b) First Sale Z-Stat	(c) Termination Parameter	(c) Termination Z-Stat	(c) First Sale Parameter	(c) First Sale Z-Stat	(d) Termination Parameter	(d) Termination Z-Stat	(d) First Sale Parameter	(d) First Sale Z-Stat
PATENT AGE	**-0.339**	-3.671	0.171	1.602	**-0.317**	-3.121	0.210	1.785	**-0.416**	-3.456	**0.323**	1.972	**-0.328**	-2.640	0.248	1.411
PATENT AGE^2	**0.016**	2.985	-0.010	-1.612	**0.016**	2.804	-0.011	-1.490	**0.016**	2.580	-0.012	-1.636	**0.012**	2.017	-0.012	-1.458
Nature of Technology																
START-UP	**-0.936**	-4.380	**-0.650**	-2.934	**-1.101**	-4.846	**-0.580**	-2.389	**-1.159**	-4.926	**-0.561**	-2.262	-1.263	-5.401	-0.351	-1.287
PATENT SCOPE	-0.167	-0.998	0.295	1.872	-0.079	-0.425	**0.423**	2.611	-0.107	-0.561	**0.421**	2.519	-0.126	-0.684	**0.510**	2.912
PRIOR ART CITED	-0.009	-0.805	**-0.045**	-2.727	-0.014	-1.033	-0.034	-1.835	-0.021	-1.411	-0.030	-1.555	-0.020	-1.364	**-0.048**	-2.299
RADICALNESS	0.032	1.515	**0.058**	2.014	0.018	0.648	0.034	1.109	0.025	0.829	0.031	0.981	0.035	1.163	**0.077**	2.184
INDUSTRY FUNDED	-0.531	-1.957	-0 080	-0.268	**-0.739**	-2.419	-0.162	-0.485	**-0.773**	-2.512	-0.187	-0.543	**-0.666**	-2.149	-0.350	-0.977
GENERALITY	-0.002	-0.005	-0.352	-1.061	0.047	0.131	**-0.935**	-2.469	0.028	0.077	**-0.948**	-2.469	-0.264	-0.677	-0.628	-1.494
Technology classes																
DRUG PATENT					0.152	0.214	-0.479	-0.683	-0.539	-0.554	0.707	0.589	-0.372	-0.381	-0.369	-0 303
CHEMICAL PATENT					0.185	0.493	0.556	1.372	-0.587	-1.010	1.409	1.627	-0.411	-0.705	0.838	0.940
ELECTRIC PATENT					0.270	0.734	**1.058**	2.662	-0.497	-0.943	1.734	1.861	-0.492	-0.938	1.950	1.956
MECHANICAL PATENT					1.040	1.825	1.189	1.215	1.038	1.045	0.665	0.228	1.124	1.218	0.690	0.233
Appropriability Measures																
LEAD TIME					0.243	0.634	**-1.006**	-1.991	0.430	1.106	-1.019	-1.838	0.371	0.982	**-1.176**	-2.023
SECRECY					**-0.879**	-2.273	0.522	0.997	**-0.981**	-2.554	0.557	0.999	**-0.995**	-2.630	**1.109**	1.977
LEARNING					-0.033	-0.078	**1.519**	2.400	-0.105	-0.248	**1.483**	2.267	-0.032	-0.077	**1.344**	2.039
PATENT STRENGTH					**-0.869**	-2.932	**0.932**	2.578	**-0.848**	-2.805	**0.974**	2.586	**-0.795**	-2.746	**1.207**	2.981
Interaction effects																
AGE*DRUGS									0.110	0.975	-0.155	-1.279	0.068	0 594	-0.010	-0.076
AGE*CHEM									0.145	1.600	-0.104	-0.937	0.110	1.252	-0.069	-0.568
AGE*ELEC									0.144	1.631	-0.066	-0.556	0.159	1.842	-0.059	-0.457
AGE*MECH									-0.076	-0.217	0.121	0.306	-0.082	-0.239	0.124	0.304
Period Dummies																
Y1980-1984													0.424	1.137	-0 143	-0.494
Y1984-1989													**0.560**	2.007	**-1.815**	-5.343
Log Likelihood		-1125.046				-1082.583				-1077.486				-1051.264		

Table 7: Robustness of quadratic form

	(a) First Sale		(b) First Sale		(c) Termination		(d) Termination	
NAME	Parameter	**Z-Stat**	Parameter	**Z-Stat**	Parameter	Z-Stat	Parameter	**Z-Stat**
PATENT AGE	-0.007	-0.022	0.015	0.460	0.310	1.253	-0.026	-0.799
PATENT AGE^2	0.017	0.420			**-0.074**	-2.097		
PATENT AGE^3	-0.001	-0.699			**0.004**	2.541		
Log Likelihood	-1055.229		-1057.102		-1051.396		-1058.392	

Notes: In these regressions, we include patent quality controls, field dummies and appropriability measures, similar to regression 5c. For clarity, only the relevant hazard coefficients are reported. In each unreported hazard, age is assumed to follow a quadratic form. Statistically significant coefficients appear in bold.

Figure 1: Conditional probability of failure

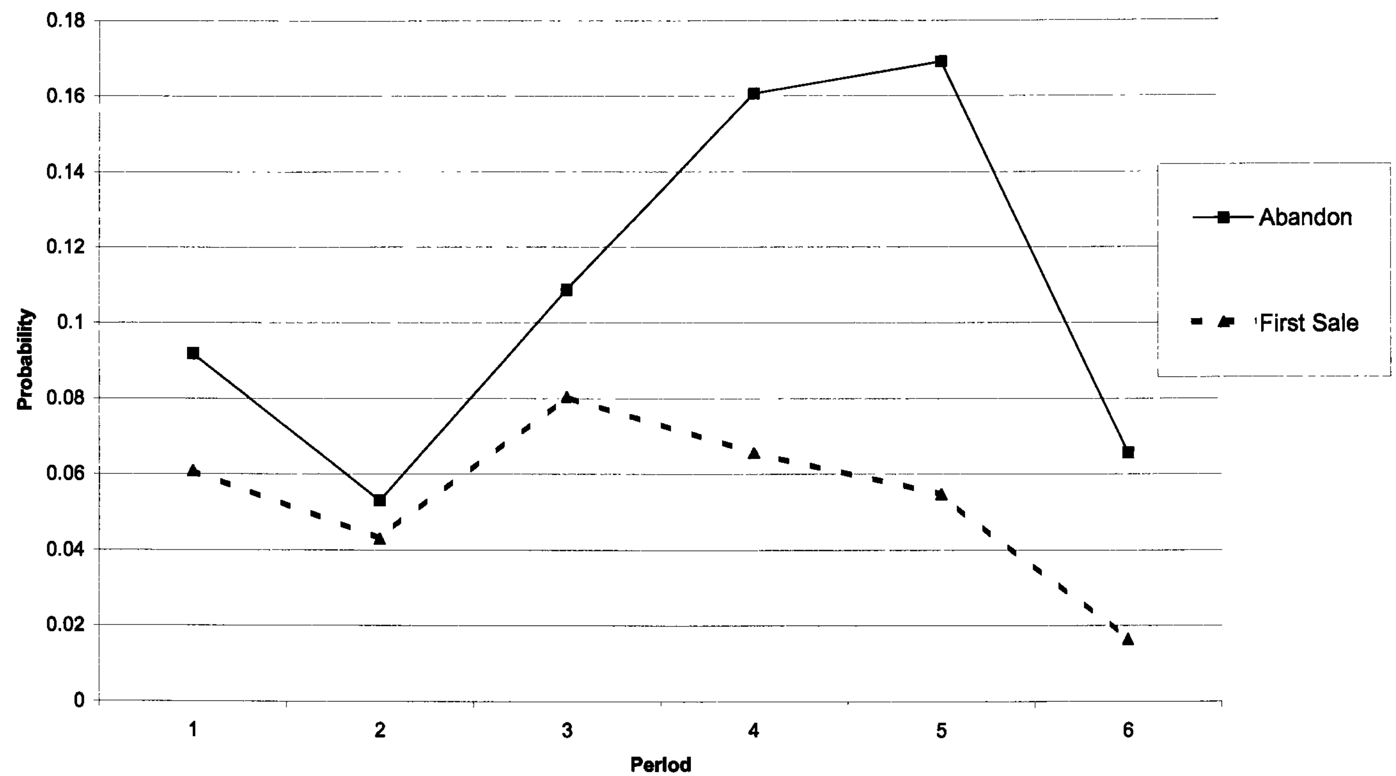


Figure 2: Change in hazard of termination with patent age

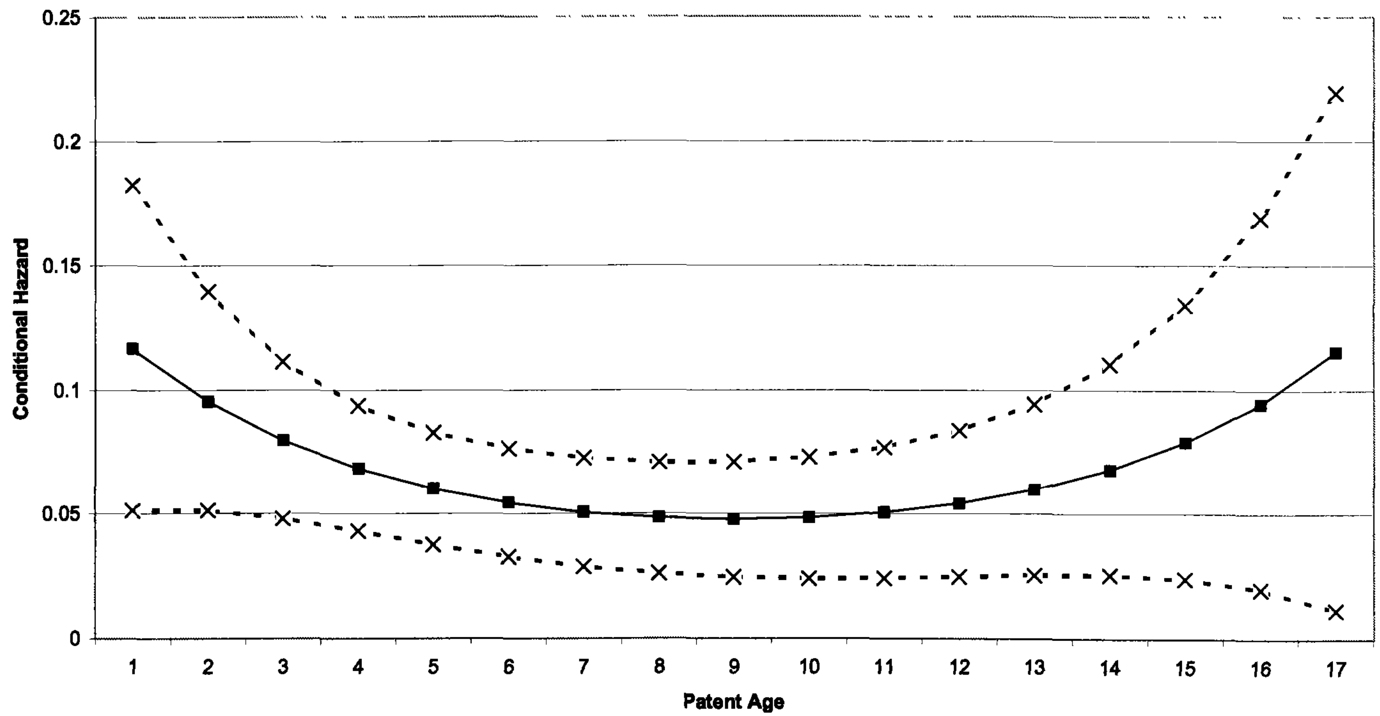
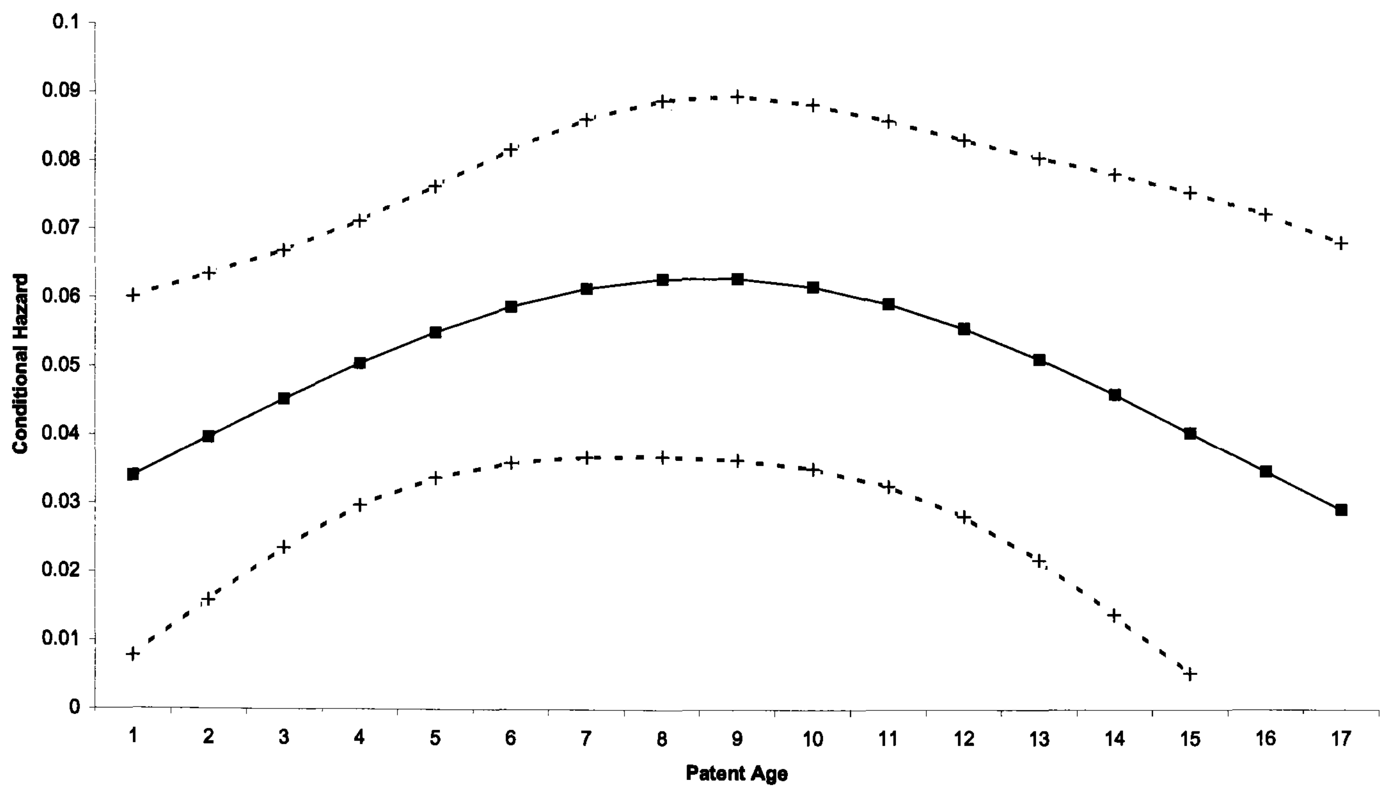


Figure 3: Change in hazard of first sale with patent age



Economic Analysis of University-Industry Collaborations: the Role of New Technology Based Firms in Japanese National Innovation Reform

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[Abstract]

In this study, quantitative analysis of university industry collaborations (UICs) is conducted in case of Japan by using the dataset from RIETI's UIC Survey and METI's Basic Survey on Business Structure and Activities. A focus is put on comparing new technology based firms (NTBFs), to large firms in terms of the characteristics of UIC activities and the impact of UICs on R&D and production productivity.

It is found that UICs are not simply adaptations of technology at university, but involves significant development activities at industry side. In this sense, UICs used to concentrate in large firm with substantial R&D resources 5 years ago. However, this activity has spread over to small firms recently, and R&D and productivity impacts of UICs can be found more clearly for small and young firm group. UIC activities by NTBFs are promising not only by the growth potential of these firms, but also by playing as agents of changes in Japan's in-house national innovation system toward network based dynamic one.

JEL Code: L25, O32, O33

Key words: University Industry Collaboration, New Technology Based Firm, Productivity, National Innovation System, Japan

1. Introduction

The second Science and Technology Basic Plan, which indicates the basic direction of Japan's science and technology policies for the period 2001 – 2006, strongly advocates national innovation system reform toward network based system by active interactions of innovation actors. Stimulating university-industry collaborations is one of core policy issues in this line. Recently, systemic reforms to strengthen the collaboration of universities and public research institutions with businesses have advanced substantially. For example, the 1998 TLO Law promoted the establishment of Technology Licensing Organizations (TLOs) in universities and public research institutions, and the Law to Strengthen Industrial Technology Capability established in 2000 includes measures for loosening restrictions on rules for researchers at public research organizations including national universities to work for private companies, and those for making it easier for national universities to receive funding from the private sector.

It is true that collaborations between university and industry become popular now in Japan. However, this movement in Japan is still lagging behind the United States, where various policy measures related to university – industry collaboration were put into place in the 1980s. This difference between two countries is mainly due to the lag of policy actions; Japan is in almost 20 years behind in the U.S. At the same time, differences in the innovation systems of Japan and the United States may also matter with the effectiveness of university industry collaborations. In the U.S., capital markets for innovation are advanced through venture capital and other means. In addition, the labor market works better than that in Japan. These factors make collaboration between industry and the public sector easier in the U.S. by utilizing external markets. Meanwhile, in Japan, a firm conducts research and development largely at its own in-house research center, and collaborations with universities and public institutions have not been put to active use. This emphasis on in-house research and development primarily at large enterprises has been pointed out as a factor impeding university industry collaboration in Japan (Motohashi, 2001).

Under these circumstances, new technology based firms (NTBFs), young and relatively small enterprises with actively engaged in research and development, may play a significant role in effective university industry collaborations in Japan. In contrast to large enterprises with significant R&D resources such as research staffs at their own research centers, NTBFs must proactively utilize external resources in their R&D efforts. According to the Survey on Japan's Innovation System conducted by the Research Institute of Economy, Trade, and Industry (RIETI), R&D–focused SMEs that proactively conduct collaborative R&D with universities perform more practical, hands-on research toward the introduction of products than do large enterprises (RIETI, 2001). In addition, compared to large enterprises, which tend to have bureaucratic decision-making organizations, SMEs can be agents of change, dynamically advancing into new fields by making speedy business decisions (Audretsch, 1999).

This paper will examine the role of NTBFs' to dynamise Japan's innovation system, which is dominated by in-house R&D, by comparing industry-university collaboration activities between large enterprises and NTBFs. University industry collaboration can take various forms, from informal technology consultation, to collaborative R&D on a contractual basis. In addition, the content of such efforts varies widely across technological field. A large-scale survey of businesses conducted in February 2003, RIETI's Survey of the University Industry Collaboration Activities investigated this heterogeneity in order to provide a clear picture of such efforts in Japan (RIETI, 2003). Based on the firm level data from this survey, we examine the difference of such efforts by the size of enterprise. In addition, by linking this dataset with the data from the Basic Survey of Japanese Business Structure and Activities of the Ministry of Economy, Trade, and Industry (METI), we analyze determinants of university industry collaborations and the impact of such efforts on firm's innovation and business performance.

This paper is structured as follows: First, in the next section we characterize the differences in university industry collaborations between large enterprises and SMEs, by using RIETI's Survey on University Industry Collaboration Activities. In section 3, we provide the results of quantitative analysis of determinants of university industry collaborations and the impacts of such efforts on firm's innovation and business performance, by using linked data of the RIETI Survey with the METI's Basic Survey of Japanese Business Structure and Activities. In the final chapter, we summarize the results of this study and conclude with discussion about the role of NTBFs in the reform of Japan's national innovation system.

2. University Industry Collaboration Activities by Firm Size

University Industry Collaboration (UIC) activities can be investigated from both the university side and the industry side. In Japan, several surveys have already been conducted on this subject. An example of a survey of universities is that conducted by Mitsubishi Research Institute (MRI) (2002). Examples of surveys of the industry side include METI (2003a), METI (2003b), and Japan Finance Corporation for Small Business (JFS) (2002). In addition, RIETI (2001) obtained data from both universities and industries on the UIC projects subject to subsidies from the New Energy and Industrial Technology Development Organization (NEDO). These surveys show the level of UIC activities, as well as their objectives, obstacles and effects. In addition, there exist some studies studying UIC activities by investigating the number of companies involved, geographical expansion of such efforts, and the numbers of projects by technology in detail

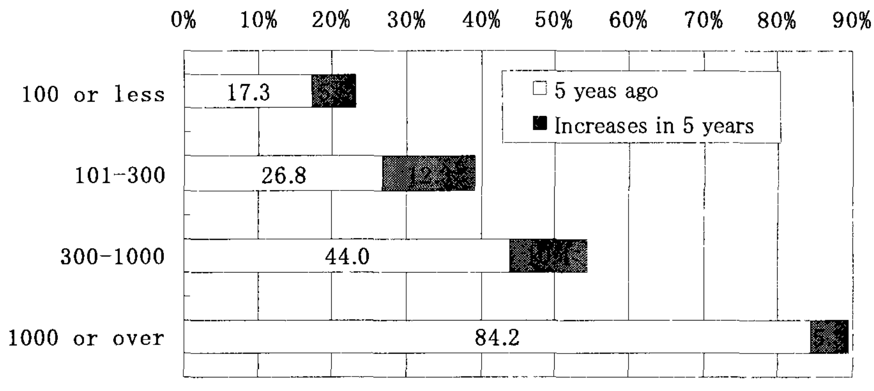
(Wen and Kobayashi, 2001). However, these examples have only provide qualitative information concerning UIC activities, and they cannot be used to quantitative analysis, such as investigating annual budgets for collaborative research and the numbers of joint research contract. Another issue with prior surveys includes a problem with sampling framework. These surveys have been limited to publicly supported UICs, or they cover only UICs for large enterprises.[1]

In contrast, RIETI's survey on UIC activities does not suffers from such sampling bias problem, since it surveys almost all firms with R&D activities in Japan (7442 firms). As a sample base, METI's Basic Survey of Japanese Business Structure and Activities, covering all firms in manufacturing, wholesale, and retail industries with fifty or more employees and capital of 30 million yen, is used. In addition, this survey covers quantitative information on UIC activities, such as an annual budget and the number of projects of UICs. The survey was conducted in February 2003 for 2002 fiscal year information, receiving valid responses from 802 firms. The survey consisted of the following three major components: (1) overall information on R&D collaboration with external bodies including other firms, universities and public research institutes, (2) detailed survey on UIC activities, including quantitative information on the size of activities, and (3) qualitative information on objectives, assessments and obstacles of UIC activities.[2] In this section, observations from this survey, focusing on dimension of the firm size variation, are provided.

First, an overall picture of R&D collaboration by firm size is presented. Approximately 70% of firms engaging in R&D activities conduct R&D collaboration in some form. Approximately 40% of firms engage in such collaboration are those with UIC activities. Although Japan's innovation system is said to be characterized by in-house R&D focus, these figures show that external collaboration in R&D is fairly widespread. This survey also compared such activities with those of five years before. Figure 1 shows the results of the shares of firms with UICs and their change from 5 years before.

[1] One of exceptions is the statistical analysis conducted for the White Paper on Small and Medium-Sized Enterprises in Japan, which covers extensive number of firms (METI, 2003b).
[2] Refer to the RIETI homepage (http://www.rieti.go.jp/jp/projects/innovation-system/index.html), for details of survey methodology including sampling methods and response rates. Although this survey's valid response rate of 10.8% is low, we simultaneously conducted a follow-up survey on non-response samples, which indicated that the effects of the non-response bias on the results were relatively small. The summary tables can be downloaded also from this site.

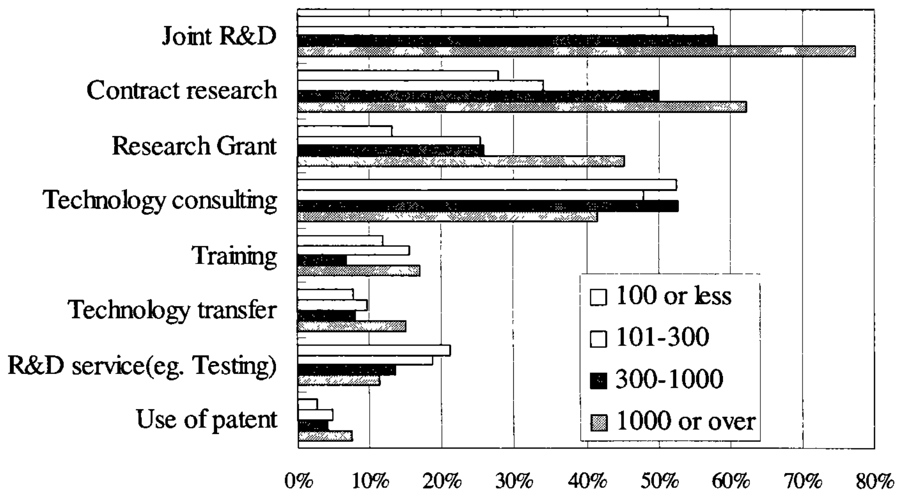
Fig. 1 Share of firms collaborating with university



One characteristic of UIC activities is that the size distribution is skewed to a greater extent, as compared to between firm collaborations. For example, while 89.5% of firms with more than 1001 employees are collaborating with universities in some form, only 23.1% of firms with 100 employees or fewer take part in such collaboration. In the case of large firms, while 65.0% of firms with more than 1001 employees are collaborating, 26.1% of firms with 100 employees or fewer take part in such collaboration. When we look at the trends in these figures over the past five years, we see that the number of smaller firms with UICs has increased faster. This survey also examines future expectation in R&D collaboration. The percentage of firms planning to strengthen collaboration with universities is 42.3% (with 51.7% planning to maintain current levels of such collaboration and 5.9% planning to reduce it), and this figure is higher than that of any collaboration with large enterprises, SMEs and national research institutes. It appears that UIC activities are spread over to smaller firms and industry has a growing expectation on UICs.

UIC activities can take various forms. They vary from formal forms of R&D collaborations, such as joint research, contracting of research and technology licensing, to more informal communication and technology consultation activities. In addition, exchanging researchers and training of personnel can be included in UIC activities as well. Figure 2 shows the share of firms taking part in each type of UIC activities by firm size.

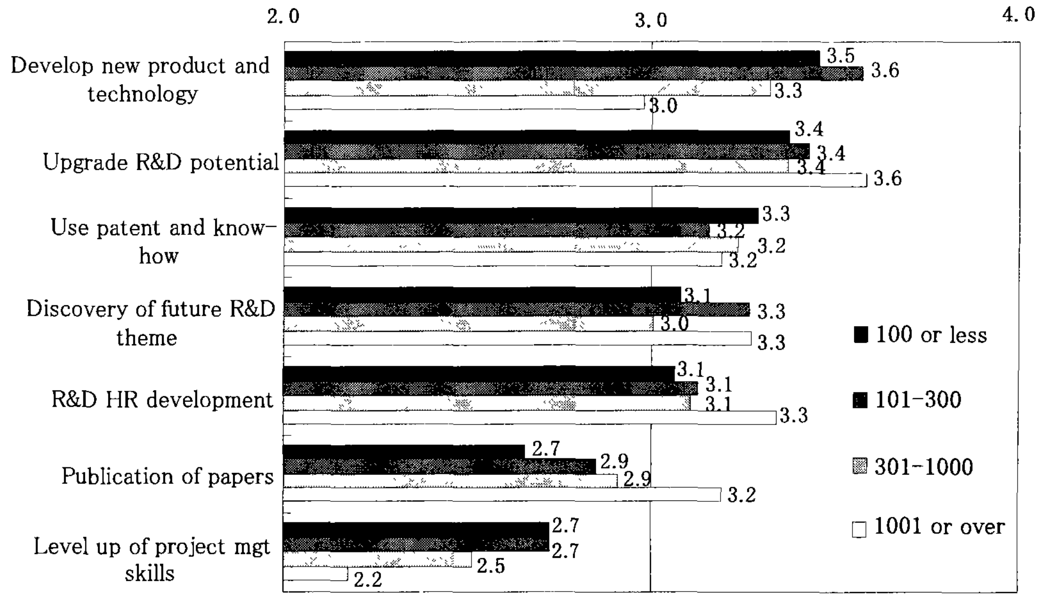
Fig. 2 Style of collaboration with university



Nearly 80% of enterprises with more than 1001 employees with UIC activities are involved in joint R&D with universities. In addition, contracted research and the provision of research grants follow. On the other hand, technology consulting is relatively popular for smaller firms. As with joint R&D, approximately half of such firms taking part in this type of activities. Regardless of firm size, the share of firms reporting the use of patents is small. It suggests that UICs are not simple existing technology adoption activities, but involve significant development activities in industry side as well, for example by contract base joint R&D.

Figure 3 shows a relative importance of objectives of UICs by firm size. Each point shows an average of the five-point Likert Scale questionnaire, and the larger the value, the more relevant as an objective of UICs.

Fig 3. Objectives of collaboration with university



While, for large enterprises with more than 1001 employees, the scores are high for upgrading one's R&D potential, smaller firms evaluate highly the development of new products and technology. When we look at this result together with those in Figure 2, we can conclude that smaller firms seek to acquire technology through technical consulting and joint R&D technology that is closer to the final product stage. In contrast, large firms, while using the same joint R&D type of collaboration, place more weight on basic and fundamental types of knowledge that can be expected to lead to long-term innovation, by seeking to upgrade their own research capabilities. One factor leading to this result may be the fact that the time scope for UIC varies between large enterprises with relatively large R&D resources such as in-house research centers, and smaller firms, which do not have such resources. An analysis of U.S. firms by Santoro and Chakrabarti (2002) shows that UICs by SMEs focus largely on resolving issues through the use of such firms' own core technologies, while those of large enterprises are intended to expand the subjects of research into new fields. The results of our survey of Japanese firms are consistent with these findings.

Smaller firms aim at the UICs intended to achieve short-term benefits such as those resulting in new products. However, it is found that the size of joint R&D for smaller firms is not always smaller than that of large firms. Table 1 shows the size of joint R&D by firm size.

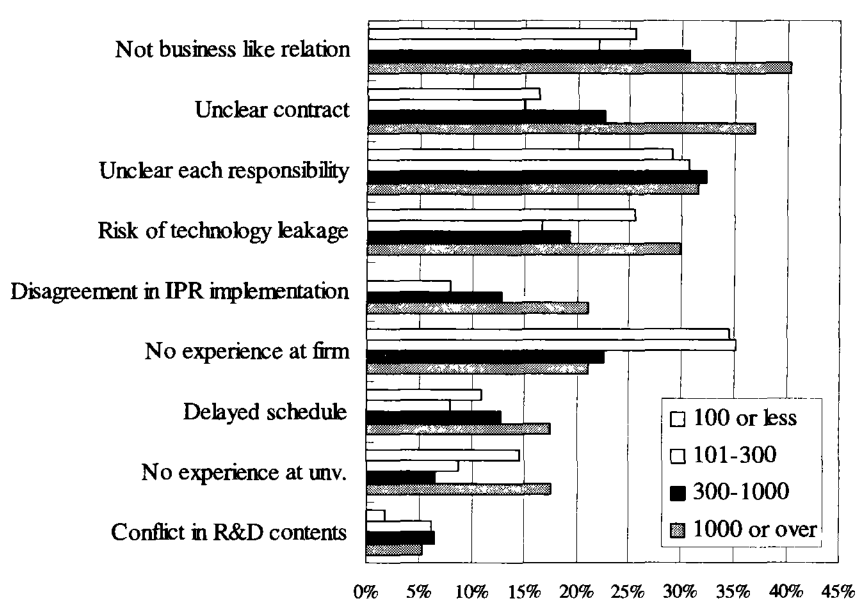
Table 1 : Collaborative R&D by firm size

	Budget per project (million yen)	Total budget	# of project	Project duration (month)	Share of public fund (%)
All	14. 1	62. 8	4. 5	13. 5	17. 8
100 or less	20. 3	34. 8	1. 7	12. 2	20. 6
101-300	14. 5	33. 9	2. 3	13. 1	19. 7
300-1000	6. 8	17. 9	2. 7	12. 8	16. 8
1000 or over	14. 2	226. 5	16. 0	16. 7	9. 9

The average per-company figures in 2002 for joint R&D budgets and the number of projects for firm conducting joint R&D are as follows: the average total budget was 62.8 million yen and the average number of projects was 4.5 per company, for an average budget of 14.1 million yen per project. When these figures are examined by firm size, the budget per project does not vary very much. While smaller firms typically conduct smaller number of project, the size of each project is not smaller. Due to the wider scope of R&D for large firms, it is natural to see that they are taking part in large numbers of UICs, presumably spreading over wide ranges of technology fields. In contrast, joint R&D project for smaller firms is more focused, but not always smaller. In addition, it is found that joint R&D projects for smaller firms are more covered by public fund than those of larger firms.

Finally, Figure 4 shows problems with UICs by firm size.

Fig. 4: Problems with R&D collaboration with university



This graph shows the percentage of firms listing each item as problem on UICs for firms conducting joint R&D. Firstly, the share of "no experience with UICs" is larger for small firms. As is already shown, UIC is not a one-way process whereby industry adopts technology and knowledge of university. Instead, industry should play an important role in innovation by providing own development resources, based on university's technology. In this sense, it is vital to increase its in-house R&D capacity, or "absorptive capacity" in Cohen and Levinthal (1989), in order to conduct effective UICs. Therefore, 'experience' matters with joint R&D with universities, and it is natural that established large firm is likely to have more experience than smaller firms, particularly new technology based firms.

On the other hand, the problems pointed out by large firms include "No business like relationship", "Unclear contract" and "Unclear each side responsibility". This problem comes from the difficulty in drawing up a clear contract covering division of each responsibility and future outcomes due to significant uncertainty associated with UIC project. Since the projects by large firms tend to cover more basic and fundamental type of contents, the degree of uncertainty and hold up problem due to incomplete contract is assumed to be larger. In addition, there may be an organizational reason as well. According to the results of RIETI survey, small firms pointed out that the roles and responsibilities of each party in carrying out the collaboration are unclear. However, only a few of them express problems with contractual issues. A small firm can overcome incomplete contract problem, because a person who is responsible for collaboration decision negotiates directly with university professors in general. On the other hand, a large firm with bureaucratic organizational structure requires a clearer contract in order to pass through internal decision making process. There are supportive evidences to this hypothesis in interview surveys for university professors involved in UICs (RIETI, 2002).

3. Determinants and impacts of university industry collaboration

(1) Data

The results of RIETI's University Industry Collaboration Survey show that large enterprises primarily use such collaboration for joint research projects aimed at strengthening their in-house technological capabilities and achieving long-term benefits, while a higher percentage of SMEs use technical consulting and take part in joint R&D aiming at projects that are closer to the final-product stage. In this section, we link the data from RIETI's Survey with ones from METI's Basic Survey of Business Structure and Activities, to quantitatively analyze the factors contributing to the decision to take part in UICs and the economic impacts of such efforts from the view point of participating enterprises. Among various styles of UICs, we proceed with our analysis focusing on university industry collaborative research.[3]

As the sample for RIETI's UIC Survey is derived from companies subject to METI's Basic Survey of Japanese Business Structure and Activities (BSBSA), the data can be linked directly. BSBSA started in 1991 and has been conducted annually since the 1994 survey. The most recent data available is that for 2000. In addition to financial-statement data for measuring the productivity and profitability of firms, it also provides innovation-related data such as R&D investment and the number of patents held, as well as three-digit industry codes and the year of establishment.

We conduct our analysis by using the linked data of RIETI's UIC Survey and METI's BSBSA for the period from 1995 to 2000. However, due to factors such as the entry and exit of firms and cut off points of BSBSA samples in terms of the number of employees and the amount of capital, the number of linked data sample varies from year to year. Table 2 shows the numbers of samples used for this analysis.

Table 2. Number of samples by timing of BSBSA

BSBSA data year	# of samples
1995	687
1996	702
1997	720
1998	759
1999	801
2000	751

(2) Determinants of UICs

A firm's decision concerning whether to take part in UICs may depend on various factors. Since the technology and know-how possessed by universities would not lead directly to new products, but would require additional R&D by firms for commercial use adaptation, firms may first need their own technological absorptive capacity. However, there is also a possibility of substitution effect of R&D resources, whereby large enterprises with significant in-house R&D resources would not take part in external collaboration involving high transaction costs. In contrast, incentives for UICs would be higher for new technology based firms (NTBFs), which tend to lack innovation-related management resources with greater necessity to seek for external technological seeds. In the U.S., there are some existing studies on UICs by size of firm. For example, Cohen et al. (2002) showed that large enterprises were more active in taking part in

[3] Refer to Bozeman (2000) for an overall review of university industry collaboration analysis.

UICs than SMEs.[4] In contrast, Acs et al. (1994) showed that, concerning innovation activities such as the introduction of new products, SMEs more effectively utilized the results of university research and that companies with poor in-house R&D resources tended to be more active in utilizing external resources.

In this section, we test various factors including firm size and age as determinants of UICs to disentangle between complementarity and substitution effecits associated with internal and external R&D resources. Table 3 shows the results of regression analysis with each of the following items as dependent variables: (1) whether the firm participated in some type of collaboration with a university in 2002; (2) whether the firm conducted joint R&D with a university in 2002; (3) the number of joint R&D projects with universities; and (4) the amount budgeted for joint R&D projects with universities (using natural logarithms). Independent variables used here are as follows.[5]

- Firm size in 2000: natural logarithm of the number of employees (BSBSA)
- R&D investment in 2000 (natural logarithm) (BSBSA)
- Amount of R&D outsourced in 2000 (natural logarithm) (BSBSA)
- Number of patents held in 2000 (natural logarithm) (BSBSA)
- Dummy variable whether firm has its own independent R&D center in 2000 (BSBSA)
- Firm age as of 2000 (natural logarithm) (BSBSA)
- Interaction terms of firm size and firm age as above
- 9 types of R&D strategy focus (see Table 3) (UIC Survey)
- 40 industry dummy variables

It should be noted that dependent variables in regression analysis here, taken from RIETI's UIC Survey are those of 2002, while most independent variables from BSBSA are those of 2000, the most recent timing of available data. Therefore we can interpret the results as correlation with 2 year lags, or simultaneous correlation by assuming that the value of independent variable is stable over time.

(Table 3)

Firstly, when we examine the results of our analysis concerning whether the firm participated in some type of collaboration with a university in 2002 and whether the firm conducted joint R&D with a university in 2002 (models 1 – 8), while the statistically significant items vary, we

[4] The exceptions were medical-related startup firms (founded within five years and with 500 employees or fewer), which actively took part in industry-academia collaboration.

obtained similar results. The values for both R&D expenditures and the number of patents held are positive and statistically significant, indicating that technological capacity is a vital factor in determining whether to take part in UICs. R&D outsourcing is also positive, indicating that, in addition to technological capacity, firms with a higher willingness to collaborate with external parties in R&D were more likely to conduct UICs. Concerning the relationship with enterprise size (log[emp]), in the models in which company age (log[age]) is not inserted, but after controlling for R&D size (log[RD]), we found statistically significant and positive coefficients. This indicates that, in addition to technological capacity, there are still some firm size effects. However, the effects of company size (log[emp]) are negative and statistically significant in the models including company age (log[age]) and the interaction of size and age. When we examine the results of this regression analysis using the partial derivative of log(emp) in order to clarify this relationship (for example, –0.80+0.29log[age] in Model 3), it is shown that the value of the coefficient was negative for young firms, indicating that the smaller a firm, the more active its participation in UICs. In the same way, when we examine the results of this regression analysis using the partial derivative of log(age) in order to examine the effects of company age (for example, -1,52+0.29log[emp] in Model 3), we find that the value of the coefficient is negative for small enterprises, indicating that the younger a firm, the more active its participation in UICs. In this way, the linear relationship between company size and participation in UICs does not hold in the group of young firms, showing tendencies similar to the characteristics of startup firms found by Cohen et al. (2002).[6]

The RIETI UIC Survey also collected the data on R&D strategy (specifically, the nine items shown in Table 3). We also analyzed the relationships between these items and UICs. Our results show that firms placing emphasis on shortening R&D lead times, focusing R&D themes, and seeking new R&D themes are more active in UICs.

Models 9 – 12 in Table 3 show the results of regression analysis using the data for the size of UICs (i.e., the number of joint R&D projects with universities and the budgeted amounts for such projects) as dependent variables. Basically, these results are similar to those for models 1 – 8. However, the effect of the number of patents held is fairly strong for models 9-12. In addition, in the models using the number of joint R&D projects as the dependent variable (model 9 and 10), no effects of enterprise size or age can be observed.

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[5] Substantial number of firms have values of 0 for two of these independent variables (the amount spent on R&D outsourcing and the number of patents held). In this case, we replace this by 1.

[6] Although the tendency of startup firms to actively take part in UICs as shown by Cohen et al. (2002) was apparent in the medical industry only, here it is indicated for the manufacturing industry as a whole

The next analysis is to investigate changes in determinants of UICs over time. As shown in Table 4, we conducted similar regression analyses using data in five years before. The RIETI UIC Survey collected the data on UIC activities five years before as well. We used this variable as a dependent variable, and used as independent variables from BSBSA in 1995, 5 years before the year 2000 in previous analysis.

(Table 4)

There are similar patterns between Table 3 and Table 4, showing the major effects of technological-capacity factors (log[RD]) and external R&D collaboration factors (RD outsourcing). Although the effects of company-size factors (log[emp]) are also apparent, unlike in the current situation, virtually no nonlinear relationship with company age is apparent. Another characteristic of the data from five year before is the fact that the coefficient for the existence of a firm's own research center, which was not statistically significant for the recent data, is both positive and statistically significant. The existence of a firm's own research center can be considered to indicate both a company's R&D capacity and investing in basic research by its own resources. These results suggest that, in five years before, a large firm with own research center were actively taking part in UICs. In order to examine the changes in determinants of UICs over the past five years, we conduct a regression analysis similar to that shown in Table 4, using a dummy variable whether a firm started UICs in this five-year period, as a dependent variable (Table 5).

(Table 5)

The existence of a firm's own research center is both negative and statistically significant in all models. In other words, companies with large R&D capacities and their own research centers had already taken part in UICs before 5 year ago, and the firms that started UICs in this five year period are mainly firms that do not have their own research centers. In addition, the coefficients of log(RD) concerning technological capacity are not statistically significant, and in Model 2, the coefficient concerning company age is negative and statically significant. These results indicate that over this five-year period, UICs have been spread to relatively small and young firms with smaller amount of own R&D resources.

(3) Impact of UICs on R&D productivity

R&D productivity can be determined by treating the amount of R&D investment as an input and development of new products and production technologies as outputs of knowledge production function. Here, we analyze the effects of UICs on the productivity of R&D activities, using the number of patents developed by a firm as an output.

We used the natural log of patents held and developed by the company as a dependent variable, and the amount of R&D investment (natural log), company size (natural log of the number of employees), the amount spent on outsourced R&D (natural log), UIC dummy variable (whether the company collaborated with a university in 1997), company age (natural log), and the interaction of the company age and the UIC dummy variable as independent variables. Tobit model is used for regressions with 40 industry dummy variables. Table 6 shows the results of our regression analysis conducted for cross-sectional data in each year from 1997 to 1999, for all variables except UIC dummy variable.[7] Next, we pooled the data from all years and conducted regression analysis, separately for three categories of firms by company age as follows[8],

- Group 1: companies founded before Japan's rapid postwar growth period (1950 or earlier)
- Group 2: companies founded during Japan's rapid postwar growth period (1951 – 1970)
- Group 3: companies founded after Japan's rapid postwar growth period (1971 or later)

(Table 6)

Due to the existence of lag between R&D inputs and outputs, it would be better to use the weighted average of time-series R&D data with an appropriate lag structure. However, it can be assumed that serial correlation is ordinarily strong in R&D data, so that using R&D data in the same timing as patent data, would not cause serious bias due to the difference in the timing. (Hall and Ziedonis, 2001) As is seen from Table 6, we have obtained fairly stable results across years of analysis, which support this assumption underlining in the analysis.

Concerning the effects of UICs on R&D productivity in cross-sectional analyses (Models 1 – 3), positive coefficients are found in all years, while statistically significant one is that only for 1999. In addition, it is observed that R&D productivity is higher for larger firms. The number of patent held and developed can be interpreted as an outcome from cumulative R&D efforts of firm. Therefore, it is natural to see the number of patent held per one-time R&D investment is higher for old and established firms.

In order to control for this age effect of R&D productivity, Models 4 – 6 in Table 5 are conducted separately by firm age category. Except for model (5), positive and statistically significant coefficients are found for UIC variable. In addition, negative and statistically

[7] In contrast to previous year data, the 2000 BSBSA did not survey the number of patents held that were developed by the company. For this reason, we conducted this analysis using data through 1999.

[8] In this regression model, we inserted data-year dummy variables in addition to industry dummy variables.

significant coefficients for the interaction terms of UIC and company age are also found in these models. In order to understand this relationship clearly, taking a partial derivative by Co-RD in Model 4 gives us the results of 11.82 – 2.94 log(age). This means that the younger a company the larger this coefficient becomes, so this result indicates that the younger a company, the greater the effects of UIC for R&D productivity. The same thing can be said to Model 6. In Model 5, which shows the results of calculation for the group of companies founded during Japan's rapid postwar growth period, a clear impact of UICs on R&D productivity cannot be observed. For this group, there are not so much variation in company age, which can explain no clear pattern in firm size and age. In addition, there may be a problem with using the patent count as a dependent variable, since the quality of each patent has not been taken into account in this analysis.[9] However, this section can be concluded that in general, UICs have a positive impact on R&D productivity and this impact become greater for younger firms.

(4) Impact of UICs on production productivity

If UIC activities increase R&D and innovation productivity, then in turn they may also affect the productivity of the firm's production activities. Our analytical framework in this section is based on production function theory, with the firm's value added serving as an output and factors of production such as labor and capital stock serving as inputs. We have estimated the following extended Cobb-Douglass production function:

$$LnVA_i = \alpha lnEMP_i + \beta lnCAP_i + \gamma lnRD_i + \mu UNIV_i + \nu UNIV_i * lnRD_i + \zeta UNIV_i * AGE_i + Ind\_dummy + \beta_i \quad (1)$$

Here, VA represents the value added; EMP represents the number of employees (not including R&D employees); CAP represents the amount of tangible fixed assets; RD represents the amount invested in R&D; UNIV is a dummy variable representing whether the firm participated in UIC five years ago (1997); AGE represents the age of the company; and ind_dummy for 40 industry dummies. Natural logarithms were used for all variables except dummy variables, and estimation was conducted using cross-sectional data from the period from 1997 to 1999. For each year, the results of this estimation with all firms included in the sample and the results with firms grouped by company age (using the same three groups as in the previous section) are presented in Table 7.

(Table 7)

[9] Concerning the quality of patents, although analysis has proceeded using patent citation data in the U.S. (Hall, Jaffe, and Trajtenberg, 2001), no database similar to that in the U.S. has been developed in Japan.

When we examine the results of analysis for all firms (Models 1, 5, and 9), we see that the intersection of UICs and R&D is positive and statistically significant for all years, indicating that the elasticity of R&D to value added is greater for firms taking part in UICs. Although the coefficient for UIC itself is positive, it is not statistically significant. From these results can be interpreted that the effects of UICs do not directly affect the productivity of all factors for the firm, but contribute to the company's performance by increasing the elasticity of R&D outputs.

When we look at the results of the analysis separately done for each firm age group, we observe that in the youngest group (the group of firms founded in 1971 or later), the coefficient of interaction term of UIC and R&D is the greatest. In other words, the effect of UIC on the elasticity of R&D outputs is particularly noticeable among young companies.

Cross section regression by using equation (1) is based on the assumption that an error term in each regression model is independent from the independent variables. However, in fact, there exist unobservable variables such as managers' capabilities and firm specific intangible asset, which are typically correlated with independent variables such as EMP, CAP and RD. In this case, the coefficients of these variables are overestimated as compared to the true values. In order to mitigate such bias, we estimated regression formula using the rates of growth of both dependent and independent variables as well. The formula used was as follows:

$$LnVA_{it}/VA_i^{t-1} = \alpha lnEMP_i/EMP_i^{t-1} + \beta lnCAP_i/CAP_i^{t-1} + \gamma lnRD_i/RD_i^{t-1} + \mu UNIV_i + \nu UNIV_i * lnRD_i/RD_i^{t-1} + Ind\_dummy + Ind\_year + \varepsilon_i \quad (2)$$

Although the independent and dependent variables are basically the same as in equation (1), each is treated here as a rate of growth. In addition, the value added was deflated by using three-digit industry deflator and the capital stock was deflated by capital stock deflator.[10] We estimated the growth rates for each of the following three periods beginning in 1997: one year (rate of growth from 1997 to 1998), two years (rate of growth from 1997 through 1999), and three years (rate of growth from 1997 through 2000).

(Table 8)

If unobserved variables in equation (1) are time invariant and this is reasonable assumption in a short period, model (2) provides consistent coefficients for each independent variable. However, another problem associated with fixed effect transformation comes in, i.e., attenuation effect due to errors in observations (Woodridge, 2002). For example, negative values for capital stock coefficients may be subject to this bias. In general, this effect becomes larger, the shorter the

[10] Details of deflators are described in Motohashi (2003a).

interval is and the larger the errors in variables are (Griliches and Hausman, 1986). Therefore, when we look at the results for Models 4 – 9 with longer interval, such problems should be smaller. In these models, the interaction term of UIC and R&D has a positive coefficients but not statistically significant. In contrast, we can find negative and statistically significant coefficients to the interaction term of UIC and Age. This indicates that the younger the firm, the greater the effects of UIC on the rate of growth in productivity. This finding is consistent with the results of the cross-sectional analysis shown in Table 7.

4. Conclusions

The results of our analysis are summarized as follows:

- With regard to the form of UIC activities, for large firms, a focus is put on joint research intended to provide long-term benefits such as increasing firm's in-house R&D potential. In contrast, for smaller firms, the percentage of firms conducting joint R&D and using technological consulting for achieving more practical results, such as the development of new products, is higher.

- As for determinants of UIC activities, it is observed that own R&D resource factors such as R&D investment, as well as with company-size factors, have positive relationship. However, when we insert firm's age and the interaction term of firm's size and age, it turns out that among smaller firms, the younger a firm, the more active it is in UICs.

- In term of changes in determinants of UIC activities over time, it is found that they have spread over among relatively young and small firms without their own research centers, and thus with a relatively smaller R&D capacity.

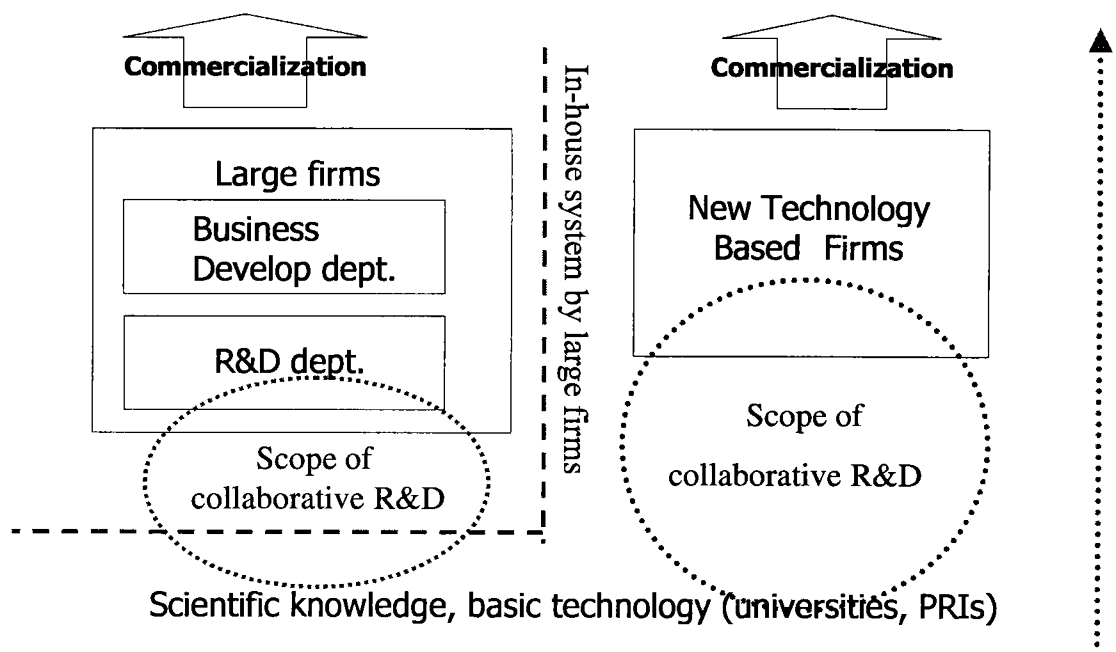
- As for UIC's impact on R&D productivity, as measured based on the number of patents held that were developed by the company, positive but not so strong impacts can be found. In addition, UICs' effects on R&D productivity are observed particularly for younger firms.

- A positive relationship exists also between UICs and the productivity of a company's production activities. Our analysis indicates that the elasticity of R&D investment outputs is higher among companies taking part in UIC activities. This tendency is more noticeable among younger firms.

Due to the nature of university, devoting its resources into fundamental research activities, it does not supply ready made technology for new product to industry. UICs are not merely technology purchasing activities, but involve significant development activities on industry side. Therefore, UICs used to be concentrated in large firms with sufficient own R&D resources in five years ago. However, UICs have been spread to smaller firm recently. New technology based firm (NTBF) becomes to have higher R&D and production productivity by UICs, as compared to other small firms. Because such firms cannot compete with large firms in terms of resources such as funding and human resources, they seem to actively take part in UICs, with more practical goals such as the development of new products. Even though NTBFs focus on practical projects, UICs not bringing commercial outcomes instantly, are risky business for them. Relatively higher premia of UICs on R&D and production productivities among young and small firms may simply reflect ex-post outcomes from risky investments. Or, only NTBFs with superior innovation management capability can take risks associated with UICs.

In any case, such firm can serve as an agent of change in context of Japan's innovation system reform, which has been dominated by large firms. Table 5 compares large firms and NTBFs in the pattern of UICs in the framework of Japan's innovation system.

Table 5. NTBFs, UICs and Japan's national innovation system



Japan's innovation system faces systemic impediments to active R&D collaboration due to inflexible labor market and underdeveloped capital and technology market. Therefore, innovation activities are mainly conducted within large firms with sufficient R&D resources from fundamental research to commercialization activities. However, it is the fact that in-house type innovation strategy for Japanese firms lead to lost in international competition in IT industries, because such innovation system does not work effectively in fields where technological advances proceed swiftly (Ando and Motohashi, 2002). Moreover, in the pharmaceuticals R&D process, which is changing rapidly due to advances in biotechnology, it is vital to effectively collaborate with universities and other institutions that have scientific knowledge in fields such as genetic engineering (Motohashi, 2003b). In-house innovation system is not effective either in this area. Therefore, Japanese innovation system needs to change toward dynamic and network based system with active external collaboration with various innovation actors.

In this sense, UIC activities by NTBFs are promising. Because NTBFs do not have extensive R&D resources, they have a strong incentive to tap on external resources, even though they have to overcome systemic impediments to networking. In addition, NTBFs needs to have clearer focus on UICs, since they cannot afford to invest in long term fundamental research project with universities. UICs by NTBFs are beneficial to university side as well. A strong policy push on Japanese universities for active commercialization of their research is put on recently, and university's professors' mind setting is gradually changing toward to active engagements in UICs for commercialization of their research. In this sense, stimulation of NTBFs' UICs can be a great momentum for the reform of whole innovation system toward network based one. Further progress in policies in this area is beneficial not only to NTBFs innovation activities but also to whole Japanese society by improving innovation environment in a world of dynamic international competition.

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Table 3: Determinants of University Industry Collaboration in 2002

	Collaboration with university in 2002 (Probit)				Joint R&D with university in 2002 (Probit)				# of co-R&D projects (Negative binominal)		Log (co-R&D budget) (Tobit)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log(employment)	**0.25** **(0.0%)**	**0.26** **(0.0%)**	**-0.80** **(7.2%)**	-0.75 (10.8%)	**0.28** **(0.0%)**	**0.27** **(0.0%)**	-0.69 (12 8%)	-0.68 (14.8%)	-0.04 (93.7%)	0.18 (70.7%)	-2.08 (12.6%)	-1.97 (14 6%)
Log(R&D investment)	**0.12** **(0.0%)**	**0.12** **(0.0%)**	**0.12** **(0.0%)**	**0.10** **(0.3%)**	**0.05** **(9.2%)**	**0.05** **(9.6%)**	**0.05** **(9.2%)**	0.03 (35.4%)	**0.07** **(8.2%)**	0.06 (19.6%)	**0.30** **(4.8%)**	0.16 (27 8%)
Log(R&D outsoucing)	**0.16** **(0.5%)**	**0.16** **(0.5%)**	**0.17** **(0.4%)**	**0.19** **(0.3%)**	0.07 (12.8%)	0.08 (12.1%)	0.08 (12.0%)	0 08 (14.8%)	**0.12** **(7.0%)**	0.11 (10.6%)	**1.47** **(0.8%)**	**1.41** **(1.1%)**
Log(# of patent owned)	**0.07** **(5.6%)**	**0.07** **(4.9%)**	0.06 (10.6%)	0.05 (18.1%)	0.04 (22.0%)	0.04 (25.9%)	0 03 (45.3%)	0.02 (64.2%)	**0.11** **(4.8%)**	**0.11** **(5.9%)**	**1.28** **(0.4%)**	**1.30** **(0.3%)**
Separate R&D center	-0.07 (71.3%)	-0.06 (73.2%)	-0.11 (54.5%)	-0.11 (56.2%)	0.04 (82.2%)	0.03 (85.1%)	-0.01 (96.6%)	-0.03 (86.4%)	0.24 (40.1%)	0.23 (41.6%)	-0.31 (62.7%)	-0.28 (65.8%)
Log(age of firm)		-0.06 (57.6%)	**-1.52** **(1.4%)**	**-1.46** **(2.4%)**		0.09 (48.7%)	**-1.24** **(4.7%)**	**-1.23** **(5.9%)**	-0.85 (21.5%)	-0.55 (43.9%)	**-3.62** **(5.5%)**	**-3.56** **(5.7%)**
Log(emp)*log(age)			**0.29** **(1.7%)**	**0.27** **(3.0%)**			**0.25** **(3.2%)**	**0.25** **(4.2%)**	0.13 (26.5%)	0.07 (56.8%)	**0.64** **(6.5%)**	**0.62** **(7.3%)**
Shorten lead-time of R&D				**0.25** **(3.7%)**				**0.23** **(6.3%)**		0.05 (78.1%)		**0.91** **(3.6%)**
Focus R&D theme				**0.24** **(4.8%)**				**0.22** **(8.2%)**		**0.36** **(6.1%)**		**0.72** **(9.3%)**
Cost reduction of R&D				-0.13 (35.0%)				0.00 (98.0%)		0.14 (55.4%)		0.01 (98 2%)
Reduction of R&D staffs				-0.01 (96.0%)				-0.08 (76.3%)		-0.18 (64.1%)		-0.48 (60.2%)
Explore new research fields				**0.57** **(0.0%)**				**0.60** **(0.0%)**		**0.71** **(0.0%)**		**1.17** **(0.7%)**
Identify marked needs				0.08 (51.0%)				**0.18** **(14.0%)**		0.06 (75.4%)		-0.05 (90 8%)
Commercialization of R&D seeds				0.23 (13.2%)				0.18 (29.0%)		0.12 (63.1%)		0.14 (80.5%)
Upgrading technology foundation				0.17 (28.4%)				-0.07 (67.3%)		0.11 (65.8%)		0.73 (19.7%)
Absorbing external technologies				0.15 (34.3%)				0.09 (57.0%)		0.06 (81.2%)		0.85 (11.1%)
Industry dummy	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
# of observations	724	724	724	724	679	679	679	679	751	751	751	751

Note: Each cell shows regression coefficient and probability > |t-value|. Bold type if it is statistically significant at 10%.

Table 4: Determinants of UIC in 1997

	Collaboration with univ. in 1997 (Probit)		
	(1)	(2)	(3)
Log(employment)	**0.22**	**0.22**	-0.33
	(0.3%)	**(0.4%)**	(48.3%)
Log(R&D investment)	**0.06**	**0.06**	**0.06**
	(8.6%)	**(8.6%)**	**(8.2%)**
Log(R&D outsoucing)	**0.24**	**0.25**	**0.25**
	(0.0%)	**(0.0%)**	**(0.0%)**
Log(# of patent owned)	**0.10**	**0.10**	**0.09**
	(2.1%)	**(2.9%)**	**(4.1%)**
Separate R&D center	**0.35**	**0.34**	0.32
	(7.1%)	**(8.4%)**	(10.7%)
Log(age of firm)		0.09	-0.70
		(47.4%)	(30.0%)
Log(emp)*log(age)			0.15
			(23.5%)
Industry dummy	yes	yes	yes
# of observations	629	628	628

Table 5: Determinants of UIC starting from 1997 to 2002

	Started collaboration with univ in these 5 years (PROBIT)		
	(1)	(2)	(3)
Log(employment)	0.04	0.06	-0.01
	(69.1%)	(49.1%)	(98.1%)
Log(R&D investment)	0.03	0.03	0.03
	(47.1%)	(48.7%)	(49.2%)
Log(R&D outsoucing)	-0.09	-0.10	-0.10
	(24.1%)	(18.9%)	(19.4%)
Log(# of patent owned)	-0.02	-0.01	-0.01
	(77.4%)	(85.3%)	(84.3%)
Separate R&D center	**-1.24**	**-1.22**	**-1.23**
	(0.4%)	**(0.4%)**	**(0.5%)**
Log(age of firm)		**-0.23**	-0.34
		(8.2%)	(67.3%)
Log(emp)*log(age)			0.02
			(89.0%)
Industry dummy	yes	yes	yes
# of observations	575	574	574

Note: Each cell shows regression coefficient and probability > |t-value|. Bold type if it is statistically significant at 10%.

Table 6: University industry collaboration and R&D productivity

	Patent (by year)			Patent (by age groups of firm)		
	1997	1998	1999	-1950	-1970	1971-
	(1)	(2)	(3)	(4)	(5)	(6)
Log(R&D investment)	**0.38** **(0.0%)**	**0.43** **(0.0%)**	**0.55** **(0.0%)**	**0.60** **(0.0%)**	**0.47** **(0.0%)**	**0.30** **(0.0%)**
Log(employment)	**0.61** **(0.0%)**	**0.59** **(0.0%)**	**0.44** **(0.0%)**	**0.48** **(0.0%)**	0.13 (21.8%)	**0.28** **(7.9%)**
R&D outsoucing	**0.17** **(1.6%)**	**0.13** **(5.9%)**	0.09 (18.7%)	**0.24** **(0.0%)**	0.04 (61.3%)	**0.23** **(1.8%)**
Co-R&D with Univ in 1997	1.43 (33.7%)	0.42 (76.6%)	**2.39** **(6.8%)**	**11.82** **(2.1%)**	-2.63 (46.9%)	**4.05** **(0.8%)**
Log(age of firm)	**0.84** **(0.1%)**	**0.58** **(1.0%)**	**0.73** **(0.2%)**	0.03 (97.4%)	0.85 (16.6%)	**1.26** **(0.0%)**
Co-RD in 97*Log(AGE)	-0.25 (54.1%)	0.05 (89.0%)	-0.47 (19.3%)	**-2.94** **(2.2%)**	0.94 (34.9%)	**-1.13** **(4.0%)**
Industry Dummy	yes	yes	yes	yes	yes	yes
Year Dummy	-	-	-	yes	yes	yes
Number of observations	707	744	786	1188	1630	819

Note: Each cell shows regression coefficient and probability > |t-value|. Bold type if it is statistically significant at 10%.

Table 7: University industry collaboration and production productivity level

	Cross section (1997)				Cross section (1998)				Cross section (1999)			
	all firms	-1950	-1970	1971-	all firms	-1950	-1970	1971-	all firms	-1950	-1970	1971-
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log(employment)	**0.77**	**0.73**	**0.73**	**0.75**	**0.78**	**0.77**	**0.73**	**0.76**	**0.75**	**0.80**	**0.70**	**0.71**
	(0.0%)	**(0.0%)**	**(0.0%)**	**(0.0%)**	**(0.0%)**	**(0.0%)**	**(0.0%)**	**(0.0%)**	**(0.0%)**	**(0.0%)**	**(0.0%)**	**(0.0%)**
Log(capital stock)	**0.18**	**0.23**	**0.23**	**0.14**	**0.17**	**0.23**	**0.20**	**0.11**	**0.18**	**0.21**	**0.22**	**0.13**
	(0.0%)	**(0.0%)**	**(0.0%)**	**(0.0%)**	**(0.0%)**	**(0.0%)**	**(0.0%)**	**(0.1%)**	**(0.0%)**	**(0.0%)**	**(0.0%)**	**(0.0%)**
Log(R&D investment)	**0.05**	**0.05**	**0.04**	**0.06**	**0.05**	0.02	**0.04**	**0.09**	**0.09**	**0.05**	**0.08**	**0.11**
	(0.0%)	**(0.1%)**	**(1.3%)**	**(0.6%)**	**(0.0%)**	(23.1%)	**(0.6%)**	**(0.1%)**	**(0.0%)**	**(2.5%)**	**(0.0%)**	**(0.1%)**
Co-R&D with Univ in 1997	0.22	-0.38	0.23	0.63	0.16	-0.35	-1.18	0.69	0.14	0.26	-0.86	-0.32
	(26.2%)	(65.6%)	(78.3%)	(20.0%)	(45.2%)	(69.1%)	(17.5%)	(27.5%)	(47.0%)	(78.2%)	(34.2%)	(42.9%)
LogRD*Co-R&D in 1997	**0.03**	0.02	0.03	**0.08**	**0.03**	0.04	0.02	0.04	**0.03**	0.02	0.04	**0.09**
	(1.1%)	(31.6%)	(18.8%)	**(4.5%)**	**(4.2%)**	(10.7%)	(35.0%)	(46.3%)	**(3.9%)**	(36.7%)	(16.5%)	**(8.5%)**
Log(Age)*Co-R&D in 1997	-0.07	0.09	-0.07	**-0.32**	-0.05	0.07	0.32	-0.27	-0.08	-0.10	0.20	0.04
	(19.6%)	(66.3%)	(77.4%)	**(5.2%)**	(35.8%)	(77.1%)	(17.7%)	(22.7%)	(14.8%)	(68.3%)	(42.4%)	(77.6%)
# of observation	705	234	318	153	741	239	333	169	786	249	351	186

Note: Each cell shows regression coefficient and probability > |t-value|. Bold type if it is statistically significant at 10%.

Table 8: University industry collaboration and productivity growth

	Growth from 1997 to 98			Growth from 1997 to 99			Growth from 1997 to 2000		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log(employment):growth	**0.49 (0.0%)**	**0.49 (0.0%)**	**0.49 (0.0%)**	**0.60 (0.0%)**	**0.59 (0.0%)**	**0.58 (0.0%)**	**0.50 (0.0%)**	**0.50 (0.0%)**	**0.49 (0.0%)**
Log(capital stock):growth	**-0.09 (10.0%)**	-0.09 (10.0%)	**-0.10 (8.7%)**	0.01 (88.8%)	0.01 (83.8%)	0.01 (88.8%)	**0.12 (0.4%)**	**0.12 (0.4%)**	**0.12 (0.5%)**
Log(R&D investment): growth	0.01 (11.1%)	0.01 (13.2%)	0.01 (13.1%)	0.01 (20.5%)	0.00 (70.9%)	0.00 (70.4%)	0.00 (50.4%)	0.01 (25.3%)	0.01 (25.1%)
Co-R&D with Univ in 19	-0.01 (74.5%)	-0.01 (76.5%)	0.23 (76.5%)	-0.02 (45.8%)	-0.03 (27.0%)	0.55 (27.0%)	0.02 (40.6%)	0.02 (44.7%)	0.54 (44.7%)
LogRD*Co-R&D in 1997 growth	- -	0.00 (76.6%)	0.00 (77.0%)	- -	0.03 (13.7%)	0.03 (20.7%)	- -	-0.01 (34.6%)	-0.01 (22.3%)
Co-R&D*Log(Age)	- -	- -	-0.06 (10.8%)	- -	- -	**-0.16 (0.1%)**	- -	- -	**-0.14 (0.8%)**
Industry dummy	yes	yes	**yes**	yes	yes	yes	yes	yes	yes
# of observations	688	688	688	705	705	705	664	664	664

Note: Each cell shows regression coefficient and probability > |t-value|. Bold type if it is statistically significant at 10%

IS ACADEMIC SCIENCE DRIVING A SURGE IN INDUSTRIAL INNOVATION? EVIDENCE FROM PATENT CITATIONS*

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ABSTRACT

What is driving the remarkable increase over the last decade in the propensity of patents to cite academic science? Does this trend indicate that stronger knowledge spillovers from academia have helped power the surge in innovative activity in the U.S. in the 1990s? This paper seeks to shed light on these questions by using a common empirical framework to assess the relative importance of various alternative hypotheses in explaining the growth in patent citations to science. My analysis supports the notion that the nature of U.S. inventive activity has changed over the sample period, with an increased emphasis on the use of the knowledge generated by university-based scientists in later years. However, the concentration of patent-to-paper citation activity within what I call the "bio nexus" suggests that much of the contribution of knowledge spillovers from academia may be largely confined to bioscience-related inventions.

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I. Introduction

Recent research points to an evident surge in innovative activity in the United States over the past fifteen years.[1] This is suggested by, among other things, a sharp rise in patent applications and patent grants that started in the late 1980s and has persisted through the end of the 1990s – a rise that has outpaced, by a considerable margin, increases in public and private R&D spending. While a large fraction of U.S. patent grants are awarded to foreign inventors, the fraction obtained by domestic inventors has risen – and this fraction has risen particularly rapidly in fields where patenting has grown most sharply. The recent patent surge could potentially be explained by an increase in the propensity of Americans to patent inventions, rather than an increase in the productivity of American research and development, but the recent research of Kortum and Lerner [1998, 2000, 2003] strongly suggests that recent trends in patenting and related data are more consistent with the latter interpretation. If this conclusion is correct, then it could help explain the widely observed increase in U.S. TFP growth in recent years.[2]

But if American R&D productivity has increased, then that raises the question of what factors are driving the increase.[3] This paper attempts to assess the importance of one possible contributing factor – increased knowledge spillovers from U.S.-based academic science. In essence, this paper is an attempt to explain the phenomenon graphed out in Figure I. This figure shows that citations made by patents granted in the United States to articles in the scientific literature increased very rapidly from the mid 1980s through the late 1990s.[4] Over this period, the number of patents granted by the U.S. Patent and Trademark Office to U.S. residents more

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1 See Jaffe and Lerner [forthcoming], Kortum and Lerner [1998], Kortum and Lerner [2000], and Kortum and Lerner [2003].

2 See Gordon [2000] and DeLong [2001].

3 The work of Kortum and Lerner [2000] has stressed the potential role of venture capital-linked firms in improving U.S. R&D output.

4 This graph does not break down growth in citations by the nationality of the inventor, but data from the 2002 *National Science and Engineering Indicators* shows that the majority of these citations are made by domestic patent applicants, and U.S.-based academic science is disproportionately likely to be cited. The fraction of citations to science made to U.S. authors has increased over this period. See also Narin et. al. [1997] and Hicks et. al. [2001].

than doubled, real R&D expenditures in the United States rose by almost 40%, and global output of scientific articles increased by about 13%, but patent citations to science *increased more than 13 times.*[5] Many at the National Science Foundation and other U.S. science policy agencies find this graph extremely interesting, because it seems to suggest – at least in some broad sense – that academic science and industrial technology are "closer" than they used to be. This could mean that publicly funded science is generating more spillovers to industrial innovation than in the past.[6] This, in turn, may have contributed in important ways to the apparent surge of innovative activity in the United States in the 1990s.

This positive interpretation of recent trends in the data is influenced by the theoretical contributions of Evenson and Kislev [1976] and the more recent analysis their work inspired, such as Adams [1990] and Kortum [1997]. In this general class of models, applied research is a search process that eventually exhausts the technological opportunities within a particular field. However, basic science can open up new "search distributions" for applied researchers, raising the productivity and the level of applied research effort – at least temporarily. Viewed through this theoretical lens, the concurrence of rapid growth in U.S. private R&D expenditures, even more rapid growth in patenting, mounting evidence of an acceleration in TFP growth, and still more rapid growth in the intensity with which U.S. patents cite academic science would all seem to suggest a response to new technological opportunities created by academic research. Not surprisingly, other advanced industrial nations are deliberately trying to foster closer connections between university-based scientific research and industrial R&D in conscious imitation of the "U.S. model."

However, increasingly strong knowledge spillovers from academic science to industrial R&D are only one of several factors that could be driving the changes illustrated in Figure I.

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5 These data come from the 2002 edition of the *National Science and Engineering Indicators*. The data on scientific article output may understate the growth in articles, but even a substantial correction of the official statistics would leave the basic message of Figure 1 essentially unchanged.

6 This interpretation has been stressed in recent editions of the *National Science and Engineering Indicators* and in the recent work of Narin et. al. [1997].

Furthermore, even if such knowledge spillovers are growing in strength, this could be happening in a number of different ways, which have different implications for public policy. A little thought and a cursory reading of the recent literature generate at least four alternative hypotheses that could explain the recent trends in the data. The first is the ***"increasing scientific fertility"*** hypothesis, which posits that more recent cohorts of scientific papers contain more discoveries that are directly applicable to industrial research and development, and that this trend holds across many fields of science. Under this hypothesis, knowledge spillovers from academia to industry are increasing primarily because of a qualitative change in the nature of the science being conducted at universities.[7]

The second is the ***"changing methods of invention"*** hypothesis, which posits that industrial inventors have changed the way they create new technology. The new approach to R&D draws more heavily on academic science than in the past, though it does not necessarily draw exclusively on the most recently published articles. This would be reflected in an increasing propensity for more recent cohorts of patents across a wide range of technical fields to cite science. Now, this increased propensity for more recent patents to cite science could very well reflect a response by firms to new "technological opportunities" generated by academic scientific breakthroughs. The point being stressed is that it is the inventors themselves who are generating the increased citations as they alter the direction and nature of their R&D programs to probe the new opportunities for industrial research created by basic science. Like the first hypothesis, this implies that knowledge spillovers from academic science are increasing over time, but the mechanism driving this increase is different.

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[7] I will note that here and elsewhere, I am being a bit loose in my use of the term "knowledge spillover." The knowledge flows from academia to industry are only pure spillovers to the extent that industrial inventors receive them for free. In fact, conversations with industry-based R&D managers suggest that investments on the part of the firm (of various kinds) are necessary in order to effectively learn from these knowledge flows – so that they are not pure spillovers. See Cohen and Levinthal [1988], Zucker et. al. [1998], and Cockburn, Henderson, and Stern [1999].

The third is the ***"changing composition of invention"*** hypothesis, which posits that invention in certain areas of technology has been closely linked to science for some time, and, likewise, some fields of science have always been frequently cited by industrial patents. Under this hypothesis, there has been disproportionate growth in patenting in frequently citing patent classes. Similarly, growth in academic publications has been biased towards those fields of science which have historically been more closely linked to industrial R&D. In other words, at the level of individual technology classes and scientific fields, there has been little change in the relationship between science and technology *per se* – rather there has been a change in the distribution of patents and papers that generates the observed increase in citations. A variant of this hypothesis notes that there has been rapid growth in patenting by universities, and that this change in the *composition of inventors* might also contribute to the growth in patent citations to science.

Strongly biased growth in frequently citing patent classes and frequently cited fields of science could itself reflect a response by both industrial inventors and academic scientists to the "technological opportunities" created by a series of fundamental scientific breakthroughs. In fact, one might find within this "nexus" of patent classes and scientific fields evidence of changing methods of invention and/or increases in scientific fertility, such that the intensity of interaction between science and invention actually grows over time. The point being stressed in this "changing composition" hypothesis is that the new technological opportunities, if they exist, are quite specific to a small number of technical and scientific fields, and one does not observe a broad-based change across fields of technology or fields of science that is consistent with substantially changing methods of invention or substantially increased scientific fertility.

The fourth hypothesis is the ***"attorney-driven"*** hypothesis, which posits that the change in patent citations is entirely driven by changes in citations practices. For various strategic reasons connected to the desire to impress patent examiners, the fear of subsequent litigation, or both, patent lawyers have instructed their clients to increase the number of citations made to the scientific literature. The increasing availability of data on the scientific prior art in electronic form has lowered the costs of such citations, further contributing to their growth. This hypothesis, in its extreme version, suggests that little can be learned about the changing relationship between science and technology from patent citation data.

These hypotheses are not mutually exclusive, but they have quite different implications for the appropriate interpretation of the growth in patent citations to papers. In order to understand what Figure I really means, how it relates (or not) to the recent American innovation surge, and what the appropriate policy response is, it is necessary to sort out the relative importance of these hypotheses in explaining the trend illustrated in that graph.

The rest of the paper is largely devoted to an examination of the relative importance of these hypotheses within a common empirical framework. I find that aggregate trends in the data are largely explained by a combination of the "composition hypothesis" and the "changing methods of invention" hypothesis. To a surprising extent, the measured increase in patent citations to papers is localized within a relatively narrow set of technologies and scientific fields related to biotechnology that I will term the "bio nexus." Patenting and publication in these fields has grown over time, and inventors working in these technologies have substantially increased the extent to which they build on science. Citations to science have also increased outside the bio nexus, and the relative change over time has been substantial – but the total numbers of citations outside the bio nexus remain relatively small. In the raw data, there is also ample evidence of a dramatic "attorney-driven" increase in academic citation in the mid-1990s. However, controlling for this legally-driven increase does not qualitatively affect the relative importance of changing composition and changing methods of invention. Key aspects of these conclusions are consistent with other recent papers in this area.

The next section places my approach in the context of the emerging literature on the interaction between academic science and industrial invention. I go on to describe the empirical framework employed in this paper, and report my main findings. In the concluding section, I outline some policy implications of my results and directions for future research. The main message of this paper is that increased knowledge flows from academia may have contributed significantly to the innovation surge reflected in the U.S. patent statistics, but most of that impact is confined to a narrow locus of technologies and scientific fields.

II. The Link Between Academic Science and Industrial Innovation

<u>Historical Perspective</u>

From their inception, publicly supported universities in the U.S. were focused on training students in the "practical arts."[8] In the late 19th and 20th centuries, the search for commercial applications of the preceding decades' scientific discoveries led to the early creation within American universities of new engineering disciplines, including chemical engineering, electrical engineering, and aeronautical engineering. However, progress at the scientific frontier was still dominated by European institutions until the cataclysm of World War II.

The large U.S. postwar investment in basic research, much of it concentrated in universities, and the mass migration of leading European scientists to the United States quickly established America as the leading center of frontier scientific research [Rosenberg and Nelson, 1994]. The infusion of federal funds was predicated on the notion that investment in basic science would eventually lead to useful technological invention for use in both industry and in national defense. However, early attempts to assess the strength of this connection in the postwar era suggested that relationship between "frontier" academic science and industrial invention, while obviously important, was neither close nor direct.[9]

<u>Lessons from the Recent Literature</u>

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[8] Rosenberg and Nelson [1994] provide an excellent study of the history of interaction between American universities and industry.

[9] See, for example, Derek De Solla Price [1965] and Lieberman [1978]. This view was generally supported by the Defense Department's ambitious "Project Hindsight" study of the impact of basic scientific research on weapons development, which concluded that the primary impact came not from science at the research frontier, but instead from "packed-down, thoroughly understood, carefully taught old science," such as that typically presented in textbooks or university courses. See Sherwin and Isenson [1967], from which the quoted phrase is taken, for a review of Project Hindsight.

Drawing upon a wide range of data sources and methodological approaches, the recent economics literature suggests that the linkage between frontier science and industrial technology is stronger and more direct than in the past.[10] Case studies, manager interviews, and surveys have been used to assess the magnitude of this impact, the channels through which it flows, and changes in these factors over time.[11] These studies suggest that firms perceive academic research to be an important input into their own research process, though this importance differs widely across firms and industries.[12] A second stream of recent research has undertaken quantitative studies of knowledge spillovers from academic research. Jaffe [1989] and Adams [1990] were early contributors to this literature. More recently, Jaffe et. al. [1993, 1996, 1998] have used data on university patents and citations to these patents to quantify knowledge spillovers from academic science.[13] While patenting by universities has increased substantially in the United States over the last twenty years, there is evidence that as the number of university patents has grown, the marginal quality of those patents has declined.[14]

A related stream of research has undertaken quantitative analysis of university-industry research collaboration. Contributors include Zucker et. al. [1998] and Cockburn and Henderson [1998, 2000]. A number of papers in this literature have studied "start-up" activity related to academic science or academic scientists, such as Zucker et. al. [1998] and Audretsch and Stephan [1996]. Finally, several recent studies have examined university licensing of university generated inventions, such as Barnes et al. [1998], Mowery et. al. [1998], Thursby and Thursby [2002], Shane [2000, 2001], and Lach and Schankerman [2003]. While the counts of licensed inventions have grown over time, there is also evidence that, like patents, the marginal value of licenses has

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[10] For a comprehensive literature review that covers relevant research beyond the economics journals, see Agrawal [2001].

[11] Important recent studies relying primarily on case study techniques and surveys include Mansfield [1995], Cohen et. al. [1994], Faulkner and Senker [1995], Gambardella [1995], and Agrawal and Henderson [2002].

[12] While the channels by which firms absorb the results of academic research vary across industries, the Cohen et. al. [1994] study suggests that the formal scientific literature is, on average, an important channel.

[13] Barnes, Mowery, and Ziedonis [1998] and Mowery, Nelson, Sampat, and Ziedonis [1998] have undertaken a similar study for a smaller number of universities.

[14] See Jaffe, Trajtenberg, and Henderson [1998] and Hicks et al. [2001].

declined as their number has increased [Thursby and Thursby, 2002]. Furthermore, this stream of literature suggests that inventions generated by universities are typically quite "embryonic" – bringing such inventions to the market requires extensive additional investment by private firms.

Using Patent Citations to Academic Science as Measures of Knowledge Spillovers

This paper will use patent citations to academic papers to measure knowledge spillovers between academic science and industrial R&D.[15] As indicators of knowledge spillovers from academia to the private sector, these data have a number of advantages. The academic promotion system creates strong incentives for academic scientists, regardless of discipline, to publish all research results of scientific merit. As a consequence, the top-ranked research universities generate thousands of academic papers each year. Similarly, inventors have an incentive to patent their useful inventions, and a legal obligation under U.S. patent law to make appropriate citations to the prior art – including academic science.

The recent research discussed in previous paragraphs indicates that, in response to the Bayh-Dole Act and other public policy measures, universities have increased the extent to which they patent the research of university-affiliated scientists. They have also increased the extent to which they license these patented technologies to private firms. Nevertheless, it is clear to observers that only a *tiny fraction* of the typical research university's commercially relevant research output is ever patented, and only a fraction of this set of patents is ever licensed.[16] To illustrate this, Figure II shows the trends over the 1988-1997 period in several alternative indices of university research output and knowledge spillovers for one of the university systems in my data set, the University of California, which includes nine separately managed campuses and a number of affiliated laboratories. The figure graphs university patents by issue year (patents), invention disclosures by year of disclosure filing (invention disclosures), new licenses of

[15] In doing so, I am building on the work of Francis Narin and his collaborators, who have pioneered the use of these data in large-sample "bibliometric" analysis. See Narin et al. [1997] and Hicks et al. [2001] for recent examples of this work.

[16] This result is also emphasized strongly in the interview-based evidence presented by Agrawal and Henderson [2002].

university technology by date of contract (licenses), the number of citations to previous university patents by issue year of the citing patent (citations to UC patents), and the number of citations to UC-generated academic papers by issue year of the citing patent (citations to UC papers). Clearly, citations to papers are far more numerous than any other indicator. This figure suggests that patent citations to academic papers may provide a much broader window through which to observe knowledge spillovers from academic science to inventive activity than any available alternative.[17]

Citations to scientific articles can reflect learning on the part of industrial inventors through multiple channels. For instance, a firm may learn about a useful scientific discovery through an informal consulting relationship with an academic scientist or through the hiring of graduate students trained by that scientist rather than through a systematic and regular reading of the professional scientific literature. Even in these cases, the confluence of academic scientists' interest in rapid publication of significant discoveries combined with firms' legal obligation to cite relevant prior art means that citations to scientific articles will often show up in patent documents, providing a "paper trail" of knowledge diffusion, even when the particular means of knowledge diffusion was something other than the publication itself.

What my methodological approach clearly fails to measure is the contribution of "old science" to industrial invention. A significant component of the consulting work undertaken by university faculty consists of helping private industry understand and apply well-established – or, "old" – scientific techniques and engineering principles, rather than helping firms incorporate the latest frontier science into their research agendas. Likewise, recent science and engineering graduates are often employed in functions that are quite far removed from the scientific frontier, but are nevertheless quite economically important to the financial success of their employers. This contribution will be completely missed by my approach. In such cases, there is no new

[17] Other recent studies using data on patent citations to scientific papers include work by Fleming and Sorenson [2000, 2001] and Lim [2001]. Neither of these studies focuses on the large change in citations to academic science over the course of the 1990s, which is the focus here.

patented invention incorporating recent science. But as the older literature on university-industry interaction has stressed, the propagation of "old" scientific and engineering knowledge to industry through training and consulting is a *long-standing feature of the American university system*. The new development stressed by the recent literature is the closer relationship between technology and relatively recent science. It is precisely this aspect of university-industry interaction that my methodological approach will most closely reflect.

III. Examining Patent Citations to Science: A Citations Function Approach

If I am to measure the relative importance of the four alternative hypotheses outlined in the introduction, then it is essential that I examine changes in patent citations to papers while controlling for growth and changes in the distribution across fields of the population of potentially cited papers, growth and changes in the distribution across fields of the population of potentially citing patents, and differences in the historical propensity for different categories of patents to cite science. While it would be impractical to do this for the universe of academic publications and U.S. patents, it has been possible for me to obtain and link the requisite data for the campuses and affiliated research units of the University of California, Stanford University, the California Institute of Technology (Caltech), and the University of Southern California. These are the principal sources of academic research in the state of California. Inference in this paper will be based on U.S. patent citations made to scientific articles generated by these institutions. There is no geographic restriction, however, on the location of the inventor of the citing patent.

The focus on California-based academic institutions as sources of science clearly limits the scope of this study, but it is also true that the geographic locus of innovative activity in the United States over the 1980s and, particularly, the 1990s, has shifted rather dramatically from the East Coast to California [Hicks et al. 2001]. One of the reasons given for this shift is the quality of the university science infrastructure in California, to which local firms are believed to have preferential access. Among other things, this paper will submit that belief to an empirical test.

Related research strongly suggests that the patterns in the citation data used in this study closely mirror national trends. In a companion paper [Branstetter 2003], I examine the *complete* set of nonpatent citations made by a random sample of 30,000 U.S. patents granted over the 1987-1997 period. I find that the distribution of patent citations to science across fields of science and technology in that random sample is very similar to that indicated in the current paper. This suggests that one of the key findings of the current paper – the concentration of patent citations to science in bioscence-related inventions – is not an artifact of my focus on California research universities. I also find a growth rate of patent citations to science in the random sample that is similar to that found in the raw data used in the current paper. Nevertheless, one must be sensitive to the potential difficulties involved in generalizing from my results to the entire American research university system. Wherever such difficulties arise, they are noted in the discussion of empirical results in sections IV and V.

From the University Science Indicators database generated by the Institute for Scientific Information, I have obtained comprehensive data on the publication of scientific articles by my sample of California research universities, by institution, year, and scientific field, from 1981-1997. These data are matched to data on patent citations made to these publications over the 1983-1999 (grant year) period, which are provided by CHI Research. CHI Research has developed a comprehensive data base of "non-patent references" made in U.S. patent documents. These references include citations to scientific journals, industrial standards, technical disclosures, engineering manuals, etc. The focus on this paper is on the subset of references made to articles appearing in peer-reviewed scientific journals. In the CHI Research database, references to scientific journals are put into a standardized format, and these data can then be matched to data on papers published in the more than 4,000 journals covered by the Science Citation Index (SCI).[18] Through this matching process, I obtain data on patent citations to peer-reviewed

[18] For a more detailed description of the database developed by CHI Research, see Narin et. al. [1997]. Further details are also available from the author upon request.

scientific articles generated by California research universities. To these data I match data on the universe of potentially citing U.S. utility patents granted over that same period, which is available from the NBER Patent Citation Database documented in Hall et. al. [2001].

Trends in scientific publications generated by California research universities for a subset of scientific disciplines are plotted in Figure III. Particularly strong growth can be observed in biomedical research, "physics" (an aggregate which includes materials sciences fields connected to semiconductors), and "engineering and technology."[19] Trends in U.S. patenting across different categories of technologies are similarly plotted in Figure IV. While patenting in all fields has increased over the sample period, particularly sharp increases can be seen in "drugs and medicine" and "computers and communications."[20]

The empirical framework I use for analyzing these data borrows from the work of Jaffe and Trajtenberg [1996, 2002]. In this framework, I model the probability that a particular patent, p, applied for in year t, will cite a particular article, a, published in year T. This probability is determined by the combination of an exponential process by which knowledge diffuses and a second exponential process by which knowledge becomes superceded by subsequent research.

This probability is referred to in the work of Jaffe and Trajtenberg [1996, 2002] as the *citation frequency*. It is a function of the attributes of the citing patent (P), the attributes of the cited article (a), and the time lag between them (t-T). It can be rendered in notation as

$$(1) \qquad p(a,P) = \alpha(a,P)\exp[-\beta_1(t-T)][1-\exp(-\beta_2(t-T))]$$

Attributes of the citing patent that I incorporate into my analysis include the application year, the technical field (based on the primary technology class assigned by the patent examiner), the type of entity owning the patent (based on the identity of the assignee), and the geographic location of the patent, based on the address of the inventor. Attributes of the cited article that I

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[19] Comparison of these data with similar data for all major American research universities shows that California academic publication closely mirrors national trends.

[20] This graph does not break down patent trends by nationality of the inventor, but the fraction of patent grants awarded to domestic inventors has risen sharply in these two rapidly growing fields.

consider include the publication year, the scientific field of the article, and the institution with which the authors were affiliated at the time of publication.

Given these data, one could sort all potentially citing patents and all potentially cited articles into cells corresponding to the attributes of articles and patents. The expected value of the number of citations from a particular group of patents to a particular group of articles could be represented as

$$(2) \qquad E[c_{tcelTSL}] = (n_{TSL})(n_{tcel})\alpha_{tcelTSL} \exp[-(\beta_1)(t-T)][1-\exp(-\beta_2(t-T))]$$

where the dependent variable measures the number of citations made by patents in the appropriate categories of grant year (t), technology class (c), institutional type (e), and location of the citing patent's inventor (l) to articles in the appropriate categories of publication year (T), scientific field (S), and particular campus (L). The α's are multiplicative effects estimated relative to a benchmark or "base" group of patents and articles. In this model, unlike the linear case, the null hypothesis of no effect corresponds to parameter values of unity rather than zero. Equation (2) can easily be rewritten as

$$(3) \qquad \frac{E[c_{tcelTSL}]}{(n_{TSL})*(n_{tcel})} = \alpha_{tcelTSL} \exp[-\beta_1(t-T)][1-\exp(-\beta_2(t-T))]$$

This is what Jaffe and Trajtenberg [1996] refer to as a *citations function*. If one adds an error term, then this equation can be estimated using nonlinear least squares. The estimating equation is thus

$$(4) \qquad p_{tcelTSL} = \alpha_t\alpha_c\alpha_e\alpha_l\alpha_T\alpha_S\alpha_L \exp[-\beta_1(t-T)][1-\exp(-\beta_2(t-T))] + \varepsilon_{tcelTSL}$$

where the dependent variable now measures the likelihood that a particular patent in the appropriate categories (grant year, technology class, institution type, and location) will cite an article in the appropriate categories (science field, source campus, and publication year).

Patents are placed into one of the following categories: computers and communications, chemicals, drugs and medicine, electronics, mechanical inventions, and a catch-all "other" category. These are the same categories for which patent growth is depicted in Figure III. Scientific articles are classified into the following fields: biology, biomedical research, chemistry, clinical medicine, engineering and technology, physics, and "other science." Patent assignees are classified into the following institutional types: public science institutions (predominantly universities, research hospitals, and government laboratories), firms, and other institutions. The division of patents on the basis of location of the inventor and the assignment of patents and papers into groups based on grant and publication year, respectively, are discussed below.

I estimate various versions of (4) using the nonlinear least squares estimation routine of the STATA software package. When doing so, I weight the observations by the square root of the product of potentially cited articles and potentially citing patents corresponding to the cell, that is

$$(5) \qquad w = \sqrt{(n_{tcel}) * (n_{TSL})}$$

This weighting scheme should take care of possible heteroskedasticity, since the observations correspond to "grouped data," that is, each observation is an average (in the corresponding cell), computed by dividing the number of citations by $(n_{tcel})*(n_{TSL})$.

IV. Evidence from the Full Sample

Localization in Time and Geographic Space

Regression results from a version of (4) run on the full sample are given in Table I. Using the parameter values from this regression, it is also possible to graph out the double exponential function implied by our parameter estimates, giving us a sense of how the "citedness" of a particular group of articles by a particular group of patents changes over time. This is graphed out for our "base case" in Figure V. The base case in this regression corresponds to patents assigned to firms, where the first inventor resides in the U.S. outside the state of California. The base patent grant period is 1983-1987, and the base publication period is 1981-

1985. The base science category is biology, the base patent category is chemistry, and the base institution is Stanford University.[21]

The shape of the curve graphically demonstrates the first key result of this section – namely that citations to academic science are, to some extent, localized in time. Citations to science appear almost immediately after article publication, and the citation function peaks at a lag of about eight years after article publication. These lags are measured here with respect to the grant date of the patent. An alternative specification measuring patents by *application* date finds a modal lag between publication and application of five to six years, implying fairly rapid spillovers of knowledge from science into industrial invention. While the estimated lag structure demonstrates that papers continue to receive some citations even at relatively long lags, the citation frequency declines steadily after the peak lag.

These results also provide evidence of concentration in geographic space. Citing patents are assigned to three categories based on the recorded addresses of the inventor: California inventors, U.S. inventors outside California, and non-U.S. inventors.[22] U.S. inventors outside California are the base category, so the coefficients imply that California-based inventors in a given technology class are nearly three times more likely to cite California academic science. Non-U.S. inventors are only about half as likely to cite California science as is the base category.

The intranational localization of knowledge spillovers implied by the California effect seems large. However, the current specification arguably does *not* control well for regional clustering of industrial R&D within the particular niches of the broad technology categories I have employed. A finer disaggregation of patent classes would likely attenuate the measured

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[21] As commonly understood, biology is an aggregate that contains components closely associated with the bio nexus (molecular biology) and components that are arguably not closely connected to "biotech" (such as population ecology). In this paper, however, I have classified the subdisciplines of biology closely connected to the bio nexus as "biomedical research." Subdisciplines that remain within the biology aggregate used in this paper include such fields as ecology and "aquatic sciences." They are not closely connected to the bio nexus and, defined this way, "biology" would seem to be a reasonable base category. Note also that the institutional boundary of campuses like Stanford is drawn to include affiliated medical schools.

[22] The NBER Patent Citation Database only includes information on the address of the first inventor listed on the patent document, so that is the basis for geographical assignment of the patent undertaken here.

degree of localization. Furthermore, as can be seen in Figure VII, it is still the case that large numbers of citations are made by inventors far from California. In fact, one sees a "bicoastal" concentration of citations, reflecting the clustering of U.S. innovative activity in the Northeast and the West Coast.

Localization of Knowledge Flows in Technology Space and the "Changing Composition" Hypothesis

I find striking differences in the incidence of citation across fields of technology. Relative to the base category (chemicals), drug/medicine patents are 2.6 times more likely to cite science, whereas all other categories are substantially less likely to cite science. The typical patent in the least likely-to-cite category, mechanical patents, is only about 1% as likely to cite science as the typical chemical patent. The estimated gap between technology categories in citation propensity is quite substantial. Note that these estimated propensities control for the number of patents in these categories over time, so that these coefficients are properly interpreted as an estimate of the differential "per-patent" propensity to cite science.

Continuing in this theme, I can also allow different categories of science to display different propensities to be cited by patented technologies. Note that the citation function specification controls for the number of "citable papers" within these science categories over time, as well as the number of potentially citing patents across fields of technology, so the coefficients on science categories are akin to a "per-paper" measure of technological fertility. The coefficients in Table I suggest that a paper in the "biomedical research" field is *about 41 times* more likely to be cited in a patent than a paper in the base category of biology. Papers in "chemistry" and "clinical medicine" are nearly five times as likely to be cited as a biology paper, while papers in the other science categories are substantially less likely to be cited than biology papers.[23] The gap between the most and the least intensely citing technology categories is a factor of nearly two hundred.

As one can see in Figure IV, "biomedical" patenting has risen sharply over my sample period, both in absolute terms and relative to patenting in other technology categories. In fact, patenting in this area has risen more than four-fold. Likewise, as Figure III indicates, there has been substantial growth in publishing in bioscience areas by California research institutions. Even controlling for this growth, biotech patents are much more likely to cite science through the sample period, and bioscience papers are much more likely than other categories to be cited. This suggests that the aggregate trends in patent citations to science are driven largely by "biotech" patents citing "bioscience" papers. While there is growing citation activity outside this "bio nexus," patent citations to science have, to date, been highly concentrated within it.

In another take on the "composition hypothesis," I have also looked at patenting by different categories of assignees: firms, public science institutions (universities, research institutes, and research hospitals), and a grab-bag category of "other institutions" in the non-profit sector. Assignment of a patent to one of these categories is based on the typography of assignees developed in the NBER patent citation database. Relative to the base category of firms, public science institutions are nearly four times as likely to cite academic science, and "other institutions" are almost twice as likely to cite academic science, according to Table I. This is unsurprising, given the connection that is likely to exist between academic science and academic patenting. Because these institutional categories accounted for a small fraction of total U.S. patenting, even by the end of my sample period, it is still the case that the vast majority of patent

[23] In results available upon request, I estimated an "academic production function" for the university systems studied in this section of the paper, in which the output measure was the count of publications generated in a scientific field by a particular campus in a particular year. This was regressed on measures of "inputs" to the research process. The results suggest that the higher "productivity" of the biomedical sciences is not driven purely by the increase in R&D funding in that field.

citations to California academic science are made by the patents of industrial firms, not universities.[24]

Evidence on "Changes in Methods of Invention"

Having incorporated fixed effects associated with the citing field of technology, the cited field of science, the cited institution, and characteristics of the citing inventor/assignee, I can also make some inference about average changes in citation patterns over time across fields. Perhaps the most interesting finding here is that the propensity to cite academic science is evidently growing over time. This can be seen by examining the pattern of coefficients on the citing patent grant year cohort terms. They increase steadily from the "base category" of 1983-87.[25] Note that I have explicitly controlled for the fact that academic publications in the heavily cited branches of science have become more numerous and that there has been an increase in patenting in fields that heavily cite academic science. These results are consistent with the view that there has been *a change in the nature of invention* such that inventors now draw more heavily on academic science.

Evidence on Attorney-Driven Changes in Patent Citations to Scientific Papers

These results could also be driven, at least in part, by an "attorney-driven" change in citation practice, and, in fact, interpretation of the measured increase in the per-patent propensity to cite academic papers is clouded by the issue of the so-called "spike patents."[26] In 1995, the effective period of monopoly granted to U.S. patent holders changed from 17 years after the grant date to 20 years from the filing date, in order to bring U.S. patent law more fully into compliance with the provisions of the TRIPs Agreement. This change took effect for patents filed after June

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[24] This statement requires some qualification. University patenting is highly concentrated in a small number of fields. By the end of my sample period, university patenting accounted for roughly 15% of health care-related patenting. That being said, the overall results in Table I are robust to the removal of patents granted to "public science institutions" (primarily universities and research hospitals) from the sample. In fact, in some ways, they become even stronger. See Table III and the discussion on page 21.

[25] This pattern is quite robust to alternative aggregations of grant years into categories. Regression results demonstrating this are available from the author upon request.

[26] This issue is also discussed in the 2002 issue of *Science and Engineering Indicators* and in Hicks et. al. [2001].

8, 1995. Patents filed prior to this deadline benefited from a "grandfather" provision – they were granted a monopoly of either 17 years from date of grant or 20 years from date of application, whichever was longer. Rejected patents re-filed after this deadline would also be subject to new evaluation criteria.

Applications submitted to the U.S. PTO more than doubled in May and June of 1995, and these applications, referred to as the "spike patents," carried an unusually large number of citations to science. This surge in patenting seems to have been driven in part by a rush to file in order to benefit from the "grandfather" timing provision. The increase in citations to science seems to have been driven in part by a desire to avoid having to refile rejected patents under the new rules. Applicants thus erred on the side of caution by making far more than the usual number of citations to scientific material. Patents applied for in this period were issued gradually over the next few years – dramatically increasing the average citations to science per patent in the overall data. Once the last of these applications was processed, average science citations per patent actually *fell*, as is illustrated in Figure VI. This kind of simple data tabulation might suggest that the connection between science and technology is weakening, after nearly a decade of rapid growth. That conclusion would be unwarranted, but it is likely that some of the movement in the aggregate data in the mid-to-late 1990s was "attorney-driven."

Within the context of my empirical approach, one potential remedy for this problem is to remove the spike patents from my data set and re-run the citations function. The results are shown in Table II, and it can be seen here (and in all subsequent tables, where the spike patents have been removed), that the basic qualitative features of the previous empirical results remain. In particular, the finding of an increase in per-patent propensity to cite scientific papers is robust to the removal of these patents.[27]

[27] Of course, removing the spike patents does not completely eliminate the possibility that measured changes in per-patent citation propensities reflect attorney-driven changes in citations practices. However, the desire the avoid litigation or impress examiners would presumably apply across different fields of technology. Likewise, the increasing availability of computerized databases, which reduce the costs of

Evidence on Changes in Scientific Fertility

In the full sample, measures of per-paper "citedness" increase, relative to the base period, in the late 1980s and early 1990s, peaking in the 1989-92 period. They then seem to decline somewhat in the most recent period, but estimated per-paper citedness remains higher than in the base period. This fact would seem to provide reasonably strong evidence for the "changes in scientific fertility" hypothesis. However, this finding is *not* robust to the exclusion of university patents from the sample. The latter point is illustrated in Table III, which presents results based on a sample that excludes both spike patents and patents assigned to universities and to other "public science institutions," a category including research hospitals that often have links to universities. As can be seen, the apparent increase in per-paper citedness evaporates with this sample restriction. Other patterns in the results, however, are robust to this sample restriction. The measured localization of spillovers within the bio nexus remains after dropping university patents, and the measured increase over time in per-patent propensity to cite science becomes more pronounced.

Summarizing the Lessons from the Full Sample

Once we exclude "spike patents," it seems that trends in the data are best explained by a combination of the "changing composition" story and the "changing methods of invention" story. However, one needs to put the relative importance of these issues into perspective. To that end, it is useful to examine Table IV, which presents results from a series of hypothesis tests. It is certainly true that the data reject the imposition of the constraint that methods of invention have not changed – or, more precisely, that per-patent propensities to cite science have not changed

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searching for scientific prior art, applies broadly across nearly all scientific fields. It is therefore striking that patent citations to science are so tightly concentrated in that narrow "nexus" of sciences and technologies where the recent literature suggests that the intellectual interaction is the strongest. Furthermore, conversations with patent attorneys indicate that, while patent attorneys and patent examiners often insert citations to previous patents unknown to the inventor into patent applications for legal, strategic, or procedural reasons, they are much less likely to insert citations to the academic literature, largely because they are much less familiar with it than is the inventor. In other words, citations to science are likely to be a purer measure of "knowledge spillovers" than are patent citations to patents. See Jaffe, Fogarty, and Banks [1998].

broadly across fields of technology. The value of the Wald test associated with this parameter restriction (see the second column, third row) is 1,256.6, and this easily exceeds the critical value of the Chi-Square distribution at the appropriate degrees of freedom. But the degradation in model fit generated by this constraint is small. Relative to the unrestricted model, the adjusted R-squared of the restricted model declines by only about 1%. This can be inferred by comparing values in the third column – the adjusted R-squared values associated with the restricted models – with the adjusted R-squared of the unrestricted model given on the next to last row.

In striking contrast, imposing the constraint that the relative propensity of different patent classes to cite science is the same causes the adjusted R-squared to fall by about 67%, and imposing this constraint and the constraint that the relative citedness of different categories of science is the same causes the adjusted R-squared to fall by about 85%, relative to the unrestricted model. In other words, changes in the distribution of patenting across technologies and changes in the distribution of publications across fields explain much more of the total variance in patent citations to science than does average changes across fields in per-patent citation behavior over time. Now, it is possible – even likely – that part of the substantial expansion in biotech patenting has been driven by increasing knowledge spillovers from university science. This is an idea that will be probed more thoroughly in the next section. Nevertheless, the scope of these increased knowledge spillovers from university science seems to be rather narrowly confined to a small set of technologies.

The evidence in Tables I-III comes from a version of the citation function in which I constrain the obsolescence parameter to be the same across categories of technology. Following Jaffe and Trajtenberg [2002], I can allow this parameter to differ across patent technology categories. Results from such a regression are omitted for reasons of space. Allowing this parameter to vary does not change the qualitative patterns in the other results. Not surprisingly, estimated obsolescence is significantly faster for computers/communications and electronics, in the sense that the differences are both qualitatively large and statistically significant.[28]

V. Evidence from Data Subsamples – the Bio Nexus vs. the IT Nexus

Partitioning the Data

For every year of my sample period, roughly 70-90% of the total citations made by patents to scientific articles are made within the bio nexus. Given the extent to which aggregate numbers of citations are driven by biotech, I break the data into a biotech-only subsample and a subsample from which papers in bioscience and patents in biotechnology are excluded.[29] This partition of the data allows me, at least in principle, to examine changes in the bioscience-biotechnology nexus in some detail. Then, I can separately estimate the key parameters of the citations function for the "non-bio" subsample, such that the parameters of diffusion, geographic concentration, etc. – constrained to be the same across fields of science and technology -- are not driven by observations in the bio nexus. The pattern of knowledge diffusion from science to invention may be quite different outside the bio nexus; partitioning the data in this way allows me to quantify those differences.[30]

Evidence from the Bio Nexus

Evidence from the bio nexus is presented in Table V. Table V maintains the same aggregation scheme across patent classes as Tables I-III, but uses only data from the bio nexus in estimating the citations function. The "biomedical research" cluster of scientific fields is broken up into the "core fields" of biochemistry, biophysics, and molecular biology on the one hand and

[28] These results are available from the author upon request.
[29] The discipline of chemistry is somewhat unique in that it includes subdisciplines that are closely connected to the bio nexus and other subdisciplines that are completely unrelated. Given this dual nature, I include chemical patents and chemistry papers in both subsamples.
[30] A potential downside to this partition is that we lose "cross-nexus" citations, such as citations made by biotech patents to papers in mathematics and computer science. It is true that we observe an increase in such cross-nexus citations over time, probably reflecting the increasing importance of such fields as "bioinformatics," but the aggregate numbers of these cross-nexus citations remain small, even in the most recent periods.

the remaining fields of biomedical research on the other. This sample excludes spike patents, but includes patents assigned to universities, research institutes, and research hospitals.

The qualitative results are similar to those estimated in the full sample. In particular, one finds, even within the bio nexus, statistically significant evidence of an increase in the per-patent propensity to cite science over time. In other words, even within this nexus, where citation activity has always been strongest and where the number of patents has been growing rapidly, the connection between industrial research and academic science seems to have grown substantially over time. The estimates on the grant year coefficients suggest that per-patent citation propensities had increased by nearly 80% (relative to the base period) by 1997-99. In this particular sample of the data, the measured increase in per-paper citedness – our measure of changes in scientific fertility – remains roughly what it was in the overall sample including public science patents. That is, it suggests an increase, albeit non-monotonic, in scientific fertility over time. While this result does not survive the exclusion of public science patents, the result of an increase in per-patent citation propensity does. Looking carefully within the bio nexus itself, one finds strong evidence of a change in the method of invention over my sample period.

The finding of an increase over time in the per-patent intensity to cite science is supported by a number of studies of the pharmaceutical and biotech industries. From its inception, the biotechnology industry has been closely linked to university-based science.[31] Furthermore, over the course of the 1980s and 1990s, established pharmaceutical companies have increasingly drawn on recent scientific developments in their efforts to improve the efficiency of their drug discovery programs.[32] While the received literature has not yet tried to *quantify* the changes in this intensity of industrial borrowing from academic science over time, the basic trends in my data are reasonably consistent with the qualitative descriptions of changes over time

[31] See Kaplan and Murray [2003], Kenney [1986], and Gambardella [1995].

[32] See, among others, Cockburn, Henderson, and Stern [1999], who provide a useful qualitative description of these changes, then go on to document their implications for relative firm performance over time within the pharmaceutical industry.

in the existing literature. Because of limitations in the time dimension of my sample, I am picking up relatively little of the impact of genomics, proteinomics, and bioinformatics on the most recent cohorts of biotech invention. While the ultimate impact of these relatively new disciplines on industrial invention remains to be seen, it is certainly possible that a future update of my regressions may find *further* acceleration of the shift in industrial invention toward greater reliance on academic science.

Have these spillovers from academic science actually raised inventive productivity in the bio nexus? A casual examination of the aggregate evidence would suggest an affirmative answer. According to NSF data, total real R&D outlays from both public and private sources associated with the life sciences nearly doubled between 1985 and 1995. However, U.S. patenting in the bio nexus more than tripled over this period, which would seem to imply a considerable increase in R&D productivity for the nexus as a whole. On the other hand, studies by others have suggested that the patent to real R&D ratio has fallen substantially for large U.S.-based pharmaceutical companies – an important component of the nexus – over much of my sample period.[33]

This discrepancy calls for careful empirical analysis of the relationship at the firm level between the incorporation of academic science into industrial R&D and its effect on research productivity. Within the bio nexus, scientific developments have apparently provided new technological opportunities for private-sector researchers to explore. The observed increase in R&D expenditures, the increase in patenting, and the striking increase in patent citations all seem to bear witness to this. It is not yet clear, however, that the new domains opened up by academic science will prove to be more fertile than the domains that preceded them. This is a point to which I will return in the concluding section and remains a focus of current research.

Evidence from the IT Nexus

The non-biotech subsample generates a significantly different pattern of results. The aggregate patent classes used are computers and communications (IT), chemistry, general

[33] See, among others, Henderson and Cockburn [1996].

electronics, mechanical inventions, and a catch-all "other" category. Science aggregates are engineering and technology, chemistry, physics, and a catch-all "other science" category. The other categories remain as before. Note that we are estimating roughly the same number of parameters for our non-biotech subsample as in the full sample, even though we have only a small fraction of the number of observations of patent-article citations. The relative thinness of the data here means that our parameter estimates need to be regarded with an extra measure of caution, even when they are statistically significant according to the conventional thresholds. Results are given in Table VI.

Patent-article citation activity outside the bio nexus is clearly concentrated in a secondary "IT" nexus. The IT patent classes cite science most frequently, displaying a propensity to cite that is nearly 18 times as high as the base category of chemistry. General electronics patents are more than 7 times as likely to cite science, while mechanical patents are three times as likely. Articles in the physics fields are more than 44 times more likely to be cited than base category (chemistry) articles. The physics aggregate includes fields that relate to semiconductors and advanced materials. The engineering/technology aggregate (which includes computer science) is the next most highly cited, with a citedness per paper that is about 8 times greater than the base category. The rest of the sciences are significantly less likely to be cited. Incidentally, these results suggest that much of the citation activity involving chemical patents and chemistry papers comes from the bio nexus. Once chemistry is separated from those technologies and disciplines, it ceases to stand out in terms of patent-article citation activity.

In a striking contrast with earlier results, geographic localization seems to be much higher in this subsample. California-based inventors display a much higher likelihood of citing California science than the base (non-California U.S.) category of inventors. While intra-national localization is much higher, *international* localization is lower – the tendency of non-American inventors to cite California science is nearly 75% as high as that of non-California American inventors, and the difference between them and the base category is not statistically significant.

This pattern of results could very well reflect the increasing geographic concentration of the U.S. information technology industry in California, as well as strong growth by inventors based outside the United States (particularly East Asia) in patenting in IT-related classes.

Another contrast with earlier results is a much higher propensity (relative to industrial firms) for patents generated by public science institutions to cite science. Public science institutions are more than 38 times as likely to cite science as are firm patents, controlling for patent category. Patents held by "other institutions," are less likely than firms to cite science in these fields, corresponding to the less significant role played by this category of assignee in non-biotech patenting.[34] The pattern of campus coefficients also highlights the unique role played by Stanford University within the sample. While, within the full sample and the bio nexus, a number of other institution's "campus effects" were nearly as high, or even higher, than Stanford's, in the non-bio subsample no other institution comes remotely close to Stanford's implied relative level of academic fertility. As with the estimates of geographic localization, it seems these data reflect the "Silicon Valley" phenomenon.

The patterns suggested by the coefficients on patent grant year cohorts and paper publication year cohorts also differ from those in previous regressions. Controlling for changes in the volume and distribution of publications and patents, all periods display a substantially greater per-patent propensity to cite science than the base period. Rather than the monotonic increase one saw in the full sample, the pattern here looks more like a step function, with a sharp increase in the late 1980s. Although the increase relative to the base period is higher than in the bio nexus, one has to keep in mind that the absolute numbers of citations in this category remains *much* smaller than in the bio nexus. The increase in per patent propensity to cite science, combined with a sharp increase in patenting in the IT-related classes, explains most of the aggregate increase in citations to science outside the bio nexus.

[34] However, dropping "public science institution" patents from the sample does not qualitatively change the nature of the other results.

While much of the recent qualitative literature on university-industry interaction has focused on the extensive borrowing from science taking place in the bio nexus, this activity is less well documented outside that nexus.[35] Nevertheless, the timing of the increase in per-patent propensity to cite science noted above is roughly coincident with two major changes in patenting – a substantial increase in patenting by semiconductor firms, especially the so-called "fabless" IC design firms, and a sharp increase in software patenting. The semiconductor industry has always had strong links to science [Hicks et al., 2001, Lim, 2003], but, as Hall and Ziedonis [2001] have showed, firms in this industry began sharply increasing their patenting in the 1980s and 1990s. Furthermore, new entrants (the so-called "fabless" design firms) emerged that were often closely linked to university engineering departments.

The increase in software patenting followed changes in U.S. patenting law and practice which expanded the ability of software inventors to patent, rather than copyright, their inventions [Bessen and Hunt, 2003]. There was little patent "prior art" to cite, so patents in this area have tended to cite more nonpatent prior art, including the relevant academic work in computer science and related fields. Software patents can be difficult to track, and the exacting timing of the measured increase depends on ones definition of a software patent. Nevertheless, some observers suggest that there was a sharp increase in software patenting at the end of the 1980s.[36]

The final result to note from our exploration of citation activity outside the bio nexus is that recent cohorts of papers are not more likely to be cited. In fact, the per-paper citedness measures have sharply plummeted, even when one includes public science patents in the sample. One can also see that the estimated obsolescence coefficient is *substantially* higher than the overall sample, while the diffusion parameter is lower. These results need to be viewed together.

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[35] Arora and Gambardella [1994] present many examples of what might be called a more "scientific" approach to industrial research outside the bio nexus, and stress the centrality of information technology in driving this shift.

[36] See Bessen and Hunt [2003] who discuss the problems involved in measuring software patenting and provide alternative counts of software patents over time. Some of these series increase quite sharply in the late 1980s.

On average, the gap between paper publication and patent citation is *much* shorter than it is in the bio nexus, such that very recent science is much more likely to get cited. Controlling for this short gap, however, there is no evidence that the most recent cohorts of papers generate more knowledge spillovers. In fact, the estimated decline in per-paper citedness is so sharp that the substantial increase in publications in these disciplines fails to make a positive contribution to total citations. In general, it seems that citations to science in these categories arrive more quickly, decay more rapidly, and peak at a lower level.

Framing these results in light of the alternative hypotheses stated in the introduction, it seems clear that the increase in citations outside the bio nexus has been driven almost entirely by composition effects – both in terms of fields of technology, fields of science, and institutions -- and "changing methods of invention." In that sense, results here are broadly consistent with those discussed earlier. However, it must be stressed that citation activity in the secondary IT nexus identified in these data is substantially lower than that within the bio nexus – so much so that the IT nexus does not even show up in the full sample. The explosion of IT patenting in recent years has been even more dramatic than that of bio nexus patenting, but the relative paucity of citations to science among these patents suggests that knowledge spillovers from academia have almost certainly *not* played the primary role in generating this patent explosion.

V. Conclusions and Extensions

What is driving the remarkable increase over the last decade in the propensity of patents to cite academic science? Does this trend indicate that stronger knowledge spillovers from academia have helped drive the surge in innovative activity in the U.S. in the 1990s? This paper has sought to shed light on these questions by using a common empirical framework to assess the relative importance of various alternative hypotheses in explaining the growth in patent citations to science. My analysis supports the notion that the nature of U.S. inventive activity has changed over the sample period, with an increased emphasis on the use of the knowledge generated by university-based scientists in later years. That being said, knowledge flows from academia to industry, as they are measured in this paper, have been overwhelmingly concentrated in the bio nexus throughout the sample period. While scientific breakthroughs generated by academic researchers, particularly in the life sciences, have generated new "technological opportunities," these new opportunities are evidently limited in scope. Stronger knowledge spillovers from academia provide, at best, only a partial explanation of the recent surge in industrial innovation evident in U.S. patent statistics.

In my introduction, I laid out four alternative hypotheses that could possibly explain the sharp increase over time in the number of patent citations to science: the "increasing scientific fertility hypothesis," the "attorney-driven" hypothesis, the "changing method of invention hypothesis," and the "changing composition of invention" hypothesis. When one excludes "public science" patents, there is little robust evidence that the scientific fertility of more recent cohorts of papers is increasing over time. There is ample evidence of dramatic "attorney-driven" fluctuations in the overall level of citation, but these can be largely linked to a one-time change in U.S. patent law in the mid-1990s, and controlling for these "attorney-driven" changes in citations practice does not affect the qualitative importance of the "changing composition" and "changing methods of invention" hypotheses in explaining overall trends in the data. It is the combination of these latter two hypotheses that are most consistent with the data.

My results also speak, albeit indirectly, to the mechanisms by which knowledge flows from universities to industry. The patenting and subsequent commercial licensing of university-generated knowledge does *not* seem to be a necessary condition for useful knowledge flows to take place. In fact, the general tenor of my results is unaltered by the removal of all patents assigned to "public science institutions" from the database. This seems to result from the fact that, even today, only a tiny fraction of the commercially relevant science generated by universities is ever patented or licensed. It does not follow from this that the recent public policy focus, in the United States and elsewhere, on the establishment of technology licensing offices in universities and the encouragement of licensing activity is necessarily misplaced. Nevertheless, the results contained herein suggest that university patents and associated licenses are neither the only nor the most important means by which university-generated knowledge is transferred to industry.

The findings of this paper also suggest some interesting avenues for future research. As I have already noted, at the current level of aggregation used in this paper, it is difficult to come to a definite conclusion about the impact of knowledge flows from academia on the research productivity of citing firms. By tracking the patents and research inputs of individual firms over time, I would be able to bring to bear all of the usual panel data econometric techniques. These could provide useful leverage in determining whether increases in the intensity of a firm's citation of academic science actually lead to substantially higher levels of innovative productivity.[37] At the firm level, I can also go much further in terms of exploring how different firms have differentially benefited from university-based scientific research. The conventional wisdom suggests that university-linked start-up firms have been an important vehicle for the mediation of knowledge flows from universities to industry. With rich, firm-specific, time-varying data on the characteristics of citing firms, one could explore these and related hypotheses much more thoroughly. Pursuing such analyses at the firm level is the focus of current research.

The results of the paper also suggest a class of theoretical models that could guide further empirical analyses. Nearly twenty years ago, Evenson and Kislev [1976] proposed a model of the interaction between basic science and applied research. I have already argued that trends in patenting and patent citations within the bio nexus seem broadly consistent with their concept of a basic scientific breakthrough opening up new "search distributions" for applied research. Further theoretical work, building on the work of Evenson and Kislev and the subsequent work they inspired, such as Kortum [1997], may prove to be a useful complement to the empirical work described above.

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[37] Preliminary empirical research by the author suggests that this is indeed the case. In keeping with the pattern of results in the current paper, the positive impact on research productivity appears to be substantially higher in the bio nexus than elsewhere.

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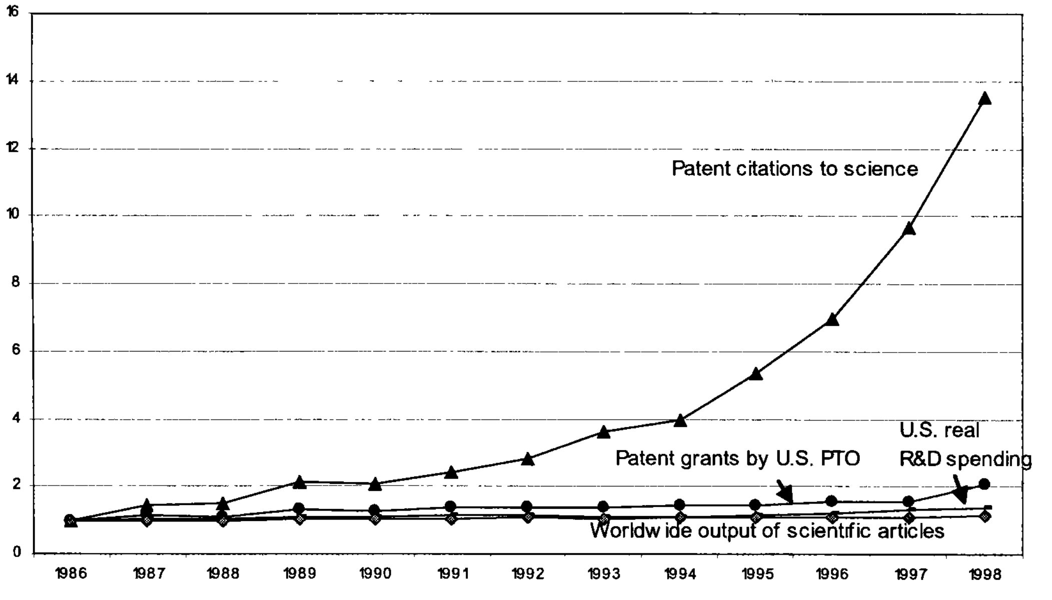
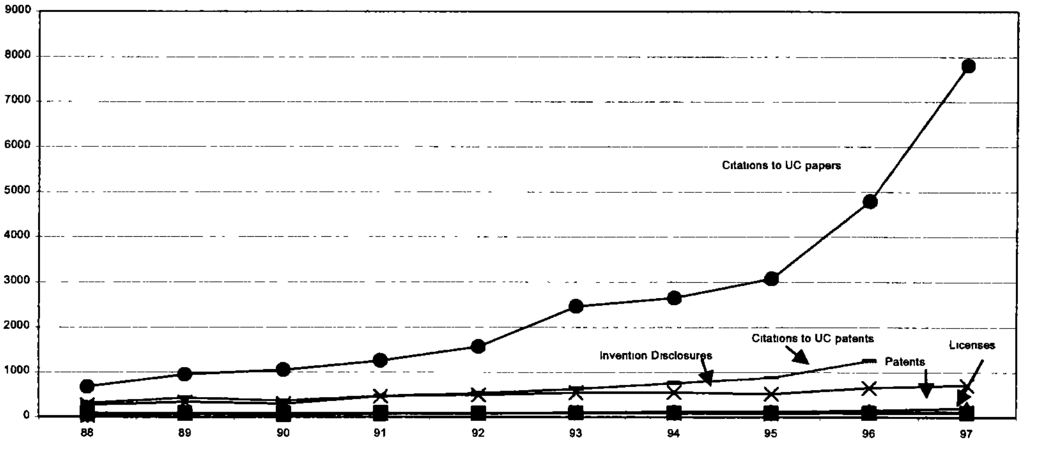
Figure I Patent Citations to Academic Science
Series are scaled so that 1986 values are equal to 1



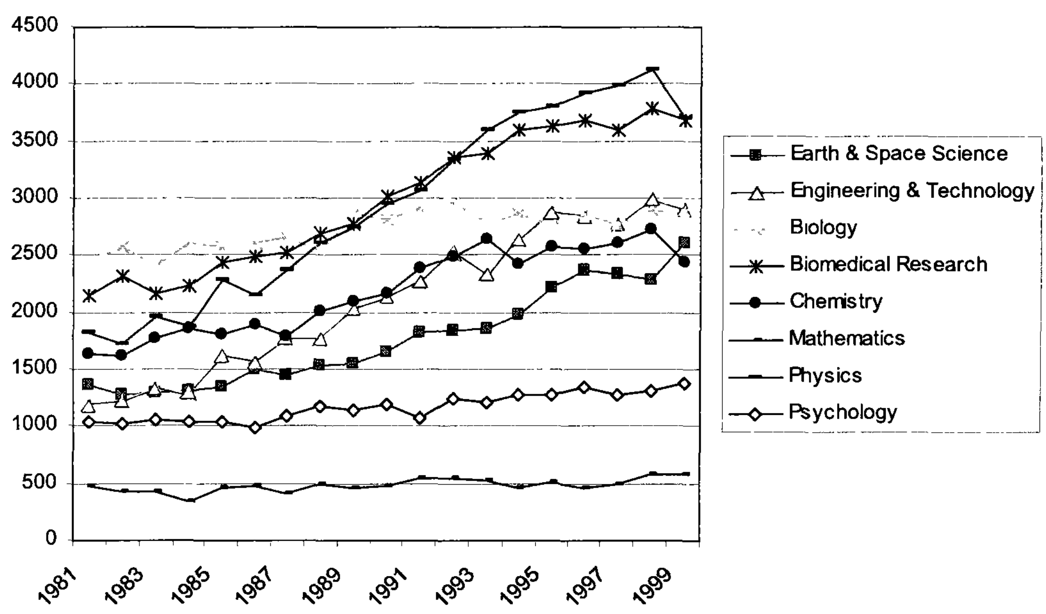
Source: National Science and Engineering Indicators, 2002

Figure II Citations to UC papers vs other indicators



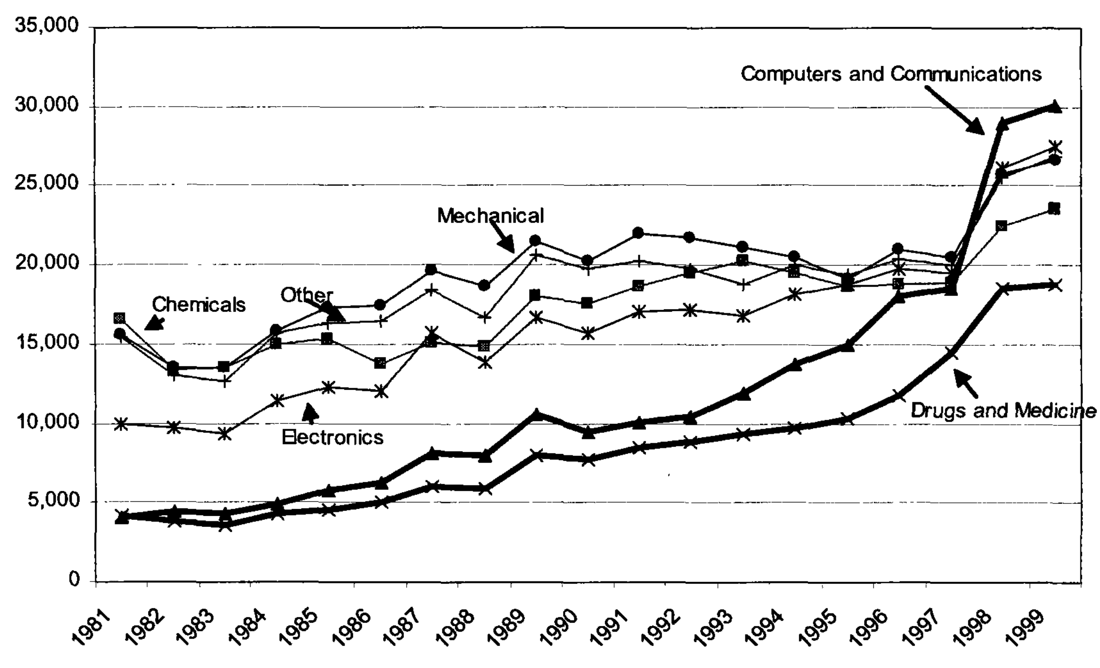
Source: Author's calculations based on data from the University of California Technology Transfer Office annual report, AUTMN, the NBER Patent Citation Data Base, and CHI Research.

Figure III
Growth in California Academic Publishing, Excluding Clinical Medicine



Source: University Science Indicators, 1999

Figure IV Patent Grants by Technology Category, 1981-1999

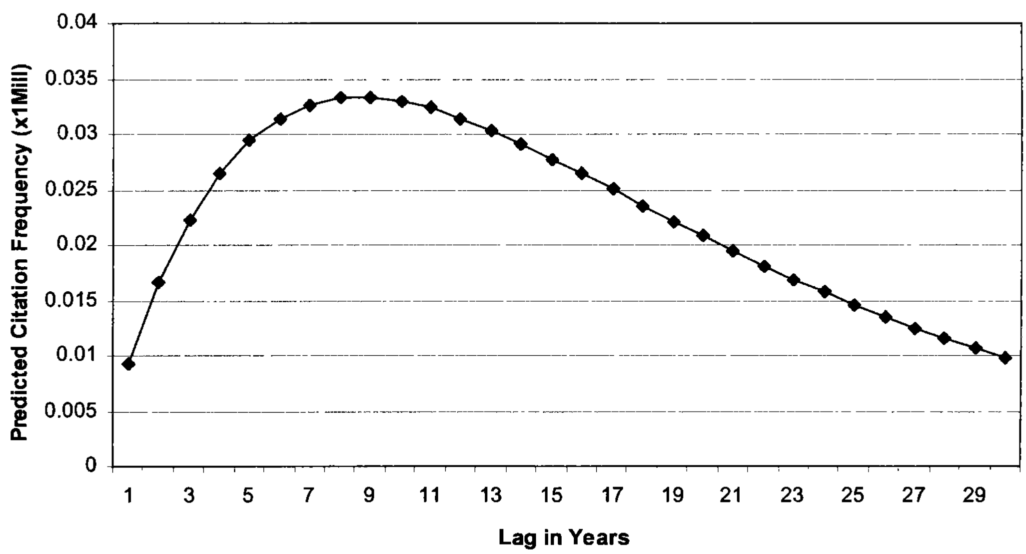


Source: NBER Patent Citation Database

Table I Citation Function Results, Full Sample

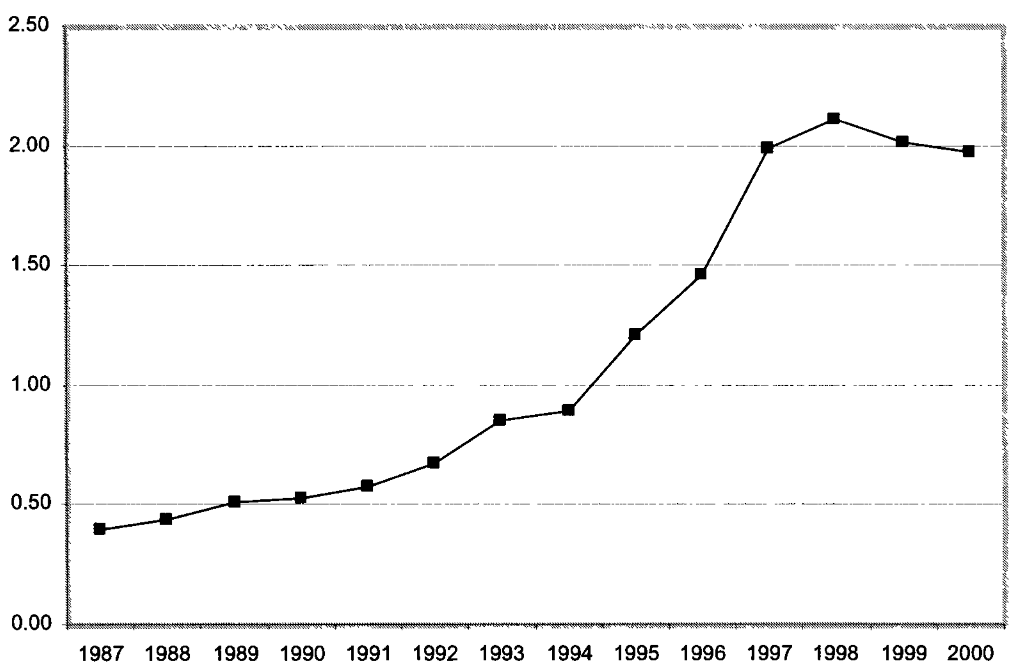
Variable	Coefficient	T-statistic for H_0: Parameter=1
Computers and Communications	0.04	-150.72
Drugs/medicine	2.44	91.93
Electronics	0.05	-157.91
Mechanical	0.01	-132.68
Other	0.05	-119.99
Biomedical research	41.02	10.11
Chemistry	4.75	8.03
Clinical Medicine	5.35	8.36
Eng/Technology	0.25	-7.94
Other Science	0.37	-7.00
Physics	0.49	-5.31
Caltech	1.19	23.93
Berkeley	0.57	-82.34
Davis	0.42	-112.52
Irvine	0.44	-93.81
Los Angeles	0.39	-128.68
Riverside	0.26	-110.96
Santa Barbara	0.29	-89.11
Santa Cruz	0.26	-87.01
San Diego	1.02	2.91
Santa Francisco	0.85	-27.36
USC	0.55	-72.01
US-CA	2.67	126.09
Non-US	0.44	-95.98
Other Institutions	1.72	44.83
Public Science	3.66	120.76
Grant year 88-90	1.02	0.95
Grant year 91-93	1.02	0.64
Grant year 94-96	1.36	10.32
Grant year 97-99	2.09	18.75
Paper pub year 85-88	1.30	26.76
Paper pub year 89-92	1.40	21.28
Paper pub year 93-97	1.10	4.78
β_1 **(obsolescence)**	0.12	75.20
β_2 **(diffusion)**	1.05E-08	10.06
Adjusted R-squared	0.220	
Number of observations	834624	

Figure V Fitted Citation Frequency (Base Category)



Source: Author's calculations.

Figure VI Average Science Citations Per Patent



Source: National Science and Engineering Indicators, 2002, National Science Foundation

Figure VII Citations to UC Berkeley Papers, US

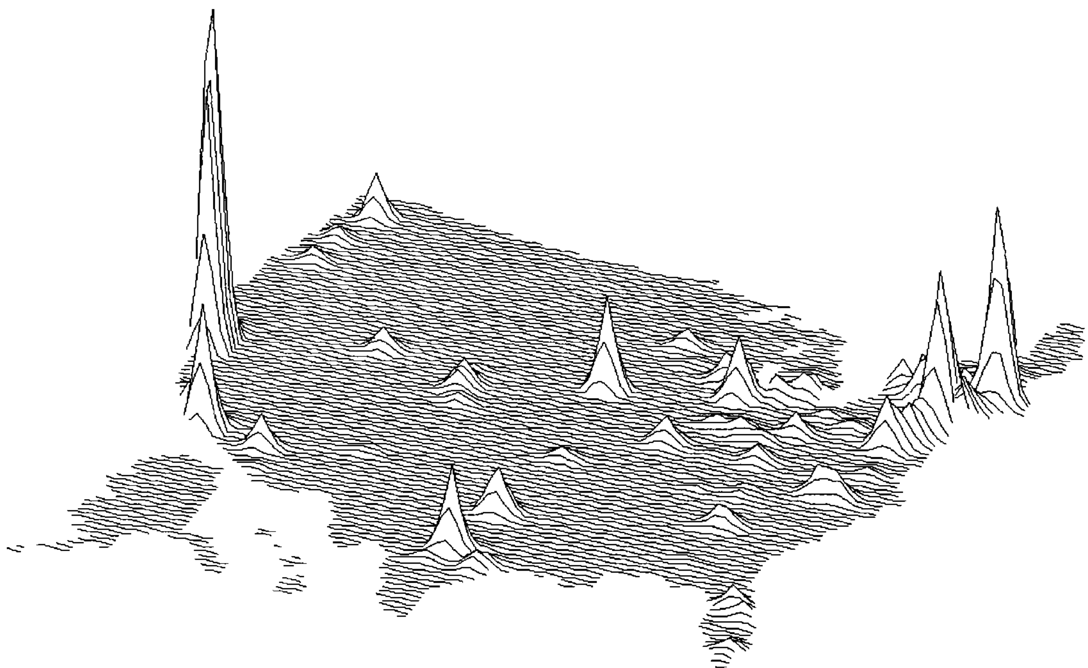


Table II Citation Function Results (excluding the patents applied in May/June 1995)

Variable	Coefficient	T-statistic for H_0: Parameter=1
Computers and Communications	0.04	-149.07
Drugs/medicine	2.29	86.30
Electronics	0.06	-157.78
Mechanical	0.01	-132.19
Other	0.05	-119.16
Biomedical research	40.67	9.43
Chemistry	5.59	7.83
Clinical Medicine	5.23	7.75
Eng/Technology	0.29	-6.99
Other Science	0.38	-6.37
Physics	0.61	-3.57
Caltech	1.15	18.36
Berkeley	0.58	-73.34
Davis	0.36	-118.03
Irvine	0.47	-82.48
Los Angeles	0.39	-119.34
Riverside	0.29	-98.94
Santa Barbara	0.30	-82.12
Santa Cruz	0.22	-85.19
San Diego	1.04	5.86
San Francisco	0.84	-26.02
USC	0.55	-67.73
US-CA	2.67	117.89
Non-US	0.45	-88.60
Other Institutions	1.72	37.49
Public Science	4.28	107.11
Grant year 88-90	1.03	1.32
Grant year 91-93	1.05	2.04
Grant year 94-96	1.42	11.54
Grant year 97-99	1.96	17.28
Paper pub year 85-88	1.31	25.15
Paper pub year 89-92	1.38	19.02
Paper pub year 93-97	1.16	6.85
β_1 **(obsolescence)**	0.122	73.44
β_2 **(diffusion)**	9.89E-09	9.42
Adjusted R-squared	0.195	
Number of observations	834624	

Base categories. Patent technology category=chemicals, scientific field=biology, academic institute=Stanford, patent assignee location=U.S./non-California, patent assignee type=firm, patent grant year=[1983, 1987], paper publication year=[1981, 1984]

Table III Citation Function Results
Full sample (excluding the patents granted to public science institutions, and the patents applied in May/June 1995)

	Coefficient	T-statistic for H_0: Parameter=1
Computers and Communications	0.039	-65.75
Drugs/medicine	4.400	44.20
Electronics	0.070	-58.35
Mechanical	0.024	-54.62
Other	0.017	-57.01
Biomedical research	82.019	2.89
Chemistry	2.559	1.69
Clinical Medicine	8.810	2.59
Engineering and Technology	0.396	-1.86
Other Science	0.502	-1.56
Physics	0.680	-0.90
Caltech	1.189	16.67
Berkeley	0.399	-84.70
Davis	0.206	-113.93
Irvine	0.242	-89.45
Los Angeles	0.333	-98.85
Santa Barbara	0.609	-32.62
Riverside	0.163	-88.64
Santa Cruz	0.181	-66.39
San Diego	0.533	-62.41
San Francisco	0.509	-72.20
USC	0.599	-43.47
US-CA	2.696	67.36
Non-US	0.375	-74.64
Other Institutions	2.196	74.20
Grant year 88-90	1.204	6.08
Grant year 91-93	1.044	1.38
Grant year 94-96	1.286	6.53
Grant year 97-99	2.221	14.03
Paper pub year 85-88	0.740	-25.99
Paper pub year 89-92	0.540	-36.42
Paper pub year 93-97	0.413	-40.76
β_1 **(obsolescence)**	0.123	45.24
β_2 **(diffusion)**	5.38E-09	2.92
Adjusted R-squared	0.118	
Number of observations	556416	

Base categories: Patent technology category=chemicals, scientific field=biology, academic institute=Stanford, patent assignee location=U.S./non-California, patent assignee type=firm, patent grant year=[1983, 1987], paper publication year=[1981, 1984]

Table IV Wald Tests of Restrictions

Hypotheses:
(1) H_0: All coefficients of patent technology categories are the same.
(2) H_0: All coefficients of paper fields are the same.
(3) H_0: All coefficients of patent grant years are the same.
(4) H_0: All coefficients of paper publication years are the same.

Hypothesis	*Test results*	
	Chi-Sq. (*p-value*)	*Adj. R^2 (rest.)*
(1)	36983.7 (0.000)	0.081
(2)	656.1 (0.000)	0.051
(1) and (2)	37639.9 (0.000)	0.028
(3)	1256.6 (0.000)	0.193
(4)	1435.8 (0.000)	0.193
Adj. R^2 (unrest).	0.195	
# of obs.	834624	

Table V
Bio Nexus Results

Variable	Coefficient	T-statistic for H_0: Parameter=1
Drugs & Medical	2.394	36.49
Chemistry	0.192	-68.28
Clinical Medicine	0.183	-96.74
Other Biotech	2.325	41.93
Caltech	0.900	-6.36
Berkeley	0.474	-45.54
Davis	0.303	-61.64
Irvine	0.367	-46.95
Los Angeles	0.364	-57.15
Riverside	0.222	-50.74
Santa Barbara	0.264	-39.76
Santa Cruz	0.241	-36.67
San Diego	0.980	-1.35
San Francisco	0.778	-17.64
USC	0.506	-33.72
US-CA	2.541	49.27
Non-US	0.443	-38.89
Other Institutions	1.586	13.50
Public Science	4.153	45.76
Grant year 88-90	1.027	0.48
Grant year 91-93	1.021	0.38
Grant year 94-96	1.364	4.57
Grant year 97-99	1.703	6.37
Paper pub year 85-88	1.298	10.68
Paper pub year 89-92	1.313	7.04
Paper pub year 93-97	1.102	1.91
β_1 **(obsolescence)**	0.113	28.78
β_2 **(diffusion)**	3.23E-07	18.17
Adjusted R-squared	0.184	
Number of observations	158976	

Base categories. Patent technology category=chemicals, scientific field=biochemistry, biophysics, and molecular biology, academic institute=Stanford, patent assignee location=U.S /non-California, patent assignee type=firm, patent grant year=[1983, 1987], paper publication year=[1981, 1984]

Table VI
Non-bio Results

Variable	Coefficient	T-statistic for H_0: Parameter=1
Computers & Communications	17.602	8.66
Electronics	7.185	7.86
Mechanical	4.539	6.94
Other	0.207	-5.50
Eng/Technology	9.289	3.07
Other Science	0.520	-1.54
Physics	44.397	3.38
Caltech	0.142	-133.39
Berkeley	0.089	-139.61
Davis	0.454	-53.52
Irvine	0.011	-105.88
Los Angeles	0.044	-131.93
Riverside	0.013	-85.92
Santa Barbara	0.039	-133.34
Santa Cruz	0.005	-81.37
San Diego	0.025	-121.39
San Francisco	0.002	-139.44
USC	0.066	-113.47
US-CA	21.629	9.85
Non-US	0.781	-1.66
Other Institutions	0.469	-1.81
Public Science	38.070	8.53
Grant year 88-90	16.349	20.87
Grant year 91-93	7.158	14.52
Grant year 94-96	15.722	13.37
Grant year 97-99	16.127	8.71
Paper pub year 85-88	0.210	-181.91
Paper pub year 89-92	0.081	-206.58
Paper pub year 93-97	0.022	-382.75
β_1 **(obsolescence)**	0.542	106.29
β_2 **(diffusion)**	5.81E-11	2.89
Adjusted R-squared	0.069	
Number of observations	397440	

Base categories: Patent technology category=chemicals, scientific field=chemistry, academic institute=Stanford, patent assignee location=U.S./non-California, patent assignee type=firm, patent grant year=[1983, 1987], paper publication year=[1981, 1984]

PRELIMINARY DRAFT

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Does the Golden Goose Travel? A Comparative Analysis of the Influence of Public Research on Industrial R&D in the U.S. and Japan.

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ABSTRACT

There is substantial concern in the U.S. and Japan about universities' and other public research institutions' contributions to national innovation systems. In both countries, there is a strong desire to strengthen ties between firms and public research. There are also those who caution that strengthening such ties may endanger the proverbial goose that lays golden eggs. Furthermore, recent debate in Japan has focused on the perceived relative weakness of Japanese universities in influencing industrial R&D. Based on comparable surveys of American and Japanese R&D labs, we compare the influence of public research on industrial R&D. We begin by showing that the institutional environment for university-industry linkages in the two countries are quite distinct. We then examine the impact of public research using a variety of survey-based measures. We find that public research has a substantial impact on industrial R&D in both countries. Furthermore, contrary to conventional wisdom, we find that the effect of public research upon industrial R&D is at least as strong overall in Japan as it is in the U.S.—and typically stronger. However, industry-by-industry comparisons show substantial heterogeneity in the patterns, with the country difference reversed in some industries, including communications equipment and automobiles. We then explore the organizational and institutional characteristics that might explain these country differences. Based on a series of logistic regressions, we show that use of public research is associated with investment in basic research, proximity to public

research centers, job rotation for engineers, and firm size. However, including these firm-level characteristics in the regressions does not eliminate the country effect. We conclude with possible explanations for the observed country effects.

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1. Introduction

There is substantial interest in the U.S. and Japan in the question of the role of university research and other public research institutions in fostering innovation and economic development. In particular, questions have been raised about how to overcome several perceived weaknesses in the ability of universities to provide assistance to industrial R&D. Policymakers in the U.S. have introduced a variety of policies designed to encourage linkages between firms and universities. These include the Bayh-Dole Act (which facilitated universities taking title of Federally funded inventions and granting exclusive licenses), CRADAs (which encouraged public-private cooperative research), the Cooperative Research Act, etc. (Heaton, et al., 1997). Similarly, the Japanese government has adopted several policies, some explicitly modeled on the new U.S. laws. These include the Technology Transfer Law (1998), which allowed the establishment of technology licensing offices (TLOs) for the national universities, additional measures that reduced patent fees for universities and relaxed the rules for professors doing work for industry, and special funding initiatives for industrial development of university inventions.

Furthermore, given the relatively weak performance of the Japanese economy in the 1990s and the widespread perception on both sides of the Pacific ocean that American universities were both scientifically stronger and more entrepreneurial, it is generally assumed that Japanese universities do a relatively poor job of contributing to industrial R&D in Japan (see, for example, Yoshihara and Tamai, 1999 for a review). For example, Cutts (1992) argues that Japanese universities are disconnected from practical influence and have become "an extreme, almost grotesque form of ivory tower." [p. 84] Brandin and Harrison (1987) claim that Japanese professors have only "a very indirect influence over industry" [p. 98], through the students they graduate and their participation on government committees, but with little direct research contact with industry. Uenohara, et al. (1984) point to the weak level of university-industry cooperation in the semiconductor industry in Japan as one reason for the development of industry R&D consortia. Mukaibo (1991) suggests that university-industry linkages in Japan are "very tenuous, to the point of being negligible"[p. 6] and points to the low rates of industry funding of university research in Japan compared to the U.S. as evidence. This perception of a gap between Japan and the U.S. underlies many of the recent policy initiatives.[1] For example, a recent presentation to AUTM by the director of University-Industry Cooperation at METI [formerly MITI] produced the follow chart (Table 1) showing the relatively lower numbers of patents, licenses and venture firms in Japan compared to the U.S., with the comment, "Compared with the U.S., **Japanese TLO's licensing rate and the number of university-based start-ups are both extremely low and, as a result, many excellent technologies are not utilized.** More support measures are needed in order to link University-Industry cooperation to economic activities." [emphasis in the original] Yet, despite these claims about the relatively weak performance of universities in Japan, prior empirical work has produced conflicting results, suggesting that Japanese universities may not under-perform compared to American universities (Hicks, 1993, Pechter, 2000).

In order to provide empirical grounding for the ongoing policy debates related to improving linkages between university research and industrial R&D, we present data from a unique dataset built on parallel surveys conducted in Japan and the U.S. We surveyed R&D managers in both countries and asked them about the influence of public research—reflecting predominantly the role of university research--as well as other outside sources, on their firms' R&D. We use these data to answer three questions. First, how important is public research for industrial R&D? Second, what are the key mechanisms for transferring information from universities and other public research institutions to firms? And, finally, how do Japan and the U.S. compare in terms of the impact of public research. We will also use these data to examine the organizational and institutional factors that might explain these country differences.

The present analysis builds on our prior work examining the influence of public research on industrial R&D in the U.S. (Cohen, et al., 2002a). The results from that analysis suggested several conclusions. First, we found that public research in the U.S. was an important source of information for industrial research. The impacts were strongest in the drug industry, but were broadly important, spanning both high-tech and mature industries. Overall, while public research was less important than customers or the firm's own manufacturing units, they were on a par with competitors as a source of

[1] Somewhat ironically, many of the American policy changes in the 1980s were the result of a perception that at that time the American innovation system was underperforming relative to Japan and that a more Japan-like system (emphasizing cooperative R&D) would improve the U.S. innovation system (Sunami, 2001).

information. We also found support for a feedback, rather than linear, model of the innovation process (cf. Kline and Rosenberg, 1986). Firms in the U.S. reported that public research was at least as important for helping complete existing projects as for suggesting new projects. We also found that the channels of open science (publications, conferences, and informal interaction) were key for transmitting scientific knowledge, with patents and licenses ranked as much less important. Finally, we found that large firms used public research more than did small firms with the important exception that startup firms were somewhat more likely to rely on public research, especially in the drug industry, with universities and other public research institutions particularly important for helping startups complete existing projects. The overall picture was one of American public research making a significant contribution to industrial R&D.

In this paper, we conduct a comparative analysis between the U.S. and Japan partly to probe the generality of our U.S. findings (Cohen et al. [2002a]), and partly to evaluate the relative impact of public research in these two important cases. Also, to the extent that the findings differ—which might be expected in light of the very different institutions, norms and policies affecting public and private research in both nations (cf. Mowery and Rosenberg [1993] and Odagiri and Goto [1993])--we can examine what factors explain these differences, with the hope of advancing our understanding of the factors affecting the role that public research plays in a national innovation system.

Although our findings reflect the influence of both universities and government research institutions, we will focus much of our discussion on the role of universities. In our prior analysis for the U.S. (Cohen et al., 2002a), our findings reflected predominantly the impact of university research rather than that conducted in government labs. We expect the same to be true for the Japanese case.[2] Thus, we

[2] We made this case for the U.S. by referring to patterns in patent citations to the scientific literature. Though a similar analysis is not available for Japan, universities appear to be the major actor here as well. For example, of the total of public research in Japan, only 30% is conducted in government research institutions, with the remainder in universities (NISTEP, 1995). A recent survey of firms in Japan showed that university linkages were mainly used to gather new knowledge or technical information, while ties to government labs were used primarily as a means of accessing specialized equipment (RIETI, 2003). Thirty-nine percent of firms reported research links with universities,

begin by describing the institutional context in which university-industry linkages are embedded in each country. We then review some of the earlier comparisons on university-industry linkages in the two countries, which can produce conflicting results, depending on the measures. We then use our survey data to show that linkages in Japan follow a pattern largely similar to that found in the U.S., with public research being important as an information source, about on par with competitors, and with the drug industry being especially close to public research. We also find that the channels of open science are key in Japan as in the U.S., and that there seems to a significant feedback component to the relationship. And, perhaps somewhat surprisingly, we find that the magnitude of the impact of public research on industrial R&D is at least as strong in Japan as it is in the U.S. We will also examine industry differences in this general pattern. Finally, we explore organizational and institutional factors that may contribute to observed differences in the influence of universities. We conclude with a discussion of the implications of our findings.

2. Institutional Context: The University System in the United States and Japan

The United States University System

The United States university system is characterized by a highly decentralized system of private and state universities that compete as peers for Federal research funds (Hanes, 1999). This external funding is key to the university's research activity, with internal funding accounting for only about 20% of total R&D (NSF, 2002).[3] Overall, government funding accounted for about 74% of R&D expenditures in 1981, declining to 66% in 1999, while industry funding increased from 4.4% to 7.3% in this same period (see Fig. 1) (NSF, 2002). In addition, not only is industry money acceptable, but consulting is common, and even encouraged, so long as it does not interfere with one's university duties. One day per week is a common norm. Unlike Japan, U.S. Federal

17% had research links to national labs, and 25% had research links to other public labs. There can be overlap in the respondents saying yes to each type of tie, so we do not know the total for all public labs. However, these data suggest that government labs in Japan play an important role in the system of public research, and we should keep this in mind when interpreting results.

[3] This percent of internal funding has increased steadily since 1960, doubling over the last 40 years.

funding often includes salary money for graduate and postdoctoral research assistants, and in some circumstances, faculty investigator salaries, as well as overhead costs for the university, in addition to the direct costs of the project. In fact, there is a category of full-time post-doctoral research personnel that are funded by project-based grants, the so-called "soft-money" positions (Heaton, et al., 1997). These positions allow universities to add (or subtract) personnel to respond to changes in the project-based funding from year to year. There is substantial variation from year to year in such funds (see Table 2, discussed below).

American universities have long had close links to industry, going back to the land grant colleges established by the Morrill Act of 1862, although there was a significant decline in the percent of industry funding in the 1960s (NSF, 2002).[4] Industry funding began returning again in the 1970s. Beginning in the 1980s (in part as a response to the perceived strengths of the Japanese innovation system) a series of policy changes were implemented that were designed to increase the flow of technology from universities and public labs to industry. Perhaps the most celebrated of these was the Bayh-Dole Act of 1980. This modification to the patent law made it much easier for universities to take title to inventions growing out of Federally funded research and to exclusively license such inventions. The Act also encourages universities to give preference to small firms when choosing licensees. A second policy initiative was the Engineering Research Centers initiative, which began in 1985. These centers were located at universities and were funded to encourage applied research and collaboration with industry. NSF has funded about 50 ERCs to date. The National Cooperative Research Act, 1984, encouraged joint research on pre-competitive technology by exempting such consortia from anti-trust prosecution. These consortia frequently include universities, further encouraging linkages.[5] The Technology Transfer Act of 1986 authorized Cooperate Research and Development Agreements (CRADAs) to allow firms to work with government labs. Again, university personnel are often part of CRADAs. The Basic Research Tax credit, added in 1986, gave firms a tax credit for outsourced R&D, encouraging firms to do research contracts with universities. Thus,

[4] Japan went through a similar decline in university-industry ties during this period.
[5] About 15% of these consortia include at least one university partner (NSF, 2002). The percentage in electronics and electrical equipment is about twice that.

during the 1980s, a series of policy initiatives in the U.S. set the stage for close university-industry linkages, including joint research, contract research and licensing of university inventions. Most of these policy initiatives focus on formalizing university-industry linkages, through, for example, research contracts or technology licenses.

These policy changes have created a system that increasingly emphasizes patenting and licensing. The result has been a substantial growth of technology transfer offices, an increase in university patenting and an increase in university licensing, including a substantial percentage of exclusive licenses. For example, in 2002, about half of licenses were exclusive, and 90% of licenses to small firms were exclusive. Universities are also increasingly taking equity stakes in startups (which often cannot pay much in licensing fees). Data from 2002 show that universities held equity in 70% of their startups, an increase from 56% the prior year (AUTM, 2002). Thus, universities increasingly find themselves in the position of not only generating ideas, but also becoming business partners in their development.

However, these policies changes appear to have had only modest effects so far on the overall influence of university research on industry. Cohen, et al. (2002a), compare firms' estimates of the importance of university research in 1983 (using the Yale survey) and 1994 (using the Carnegie Mellon survey) and find little evidence of change. Furthermore, Mowery, et al. (2001), find that the main effect of the Bayh-Dole Act may have been an increased emphasis on patenting and licensing, which many universities had avoided previously, but that there was little effect on the content of research and the effect on overall linkages is uncertain. Thursby and Thursby (2002) find that the increase in university licensing is not associated with a change in the content of university research.

Japanese University System

In Japan, most of the major research universities are national universities, under the administration of the Ministry of Culture, Education, Sports and Science (formerly under the Ministry of Education).[6] Professors at national universities are civil service

[6] As of April 1, 2004, after "agencification" [*dokuritsu-gyousei-houjinka*] the national universities will become independent public corporations (a move somewhat similar to

employees and were, until recently, severely restricted in their ability to engage in outside commercial activity (Nishizawa, 2002). There are a few private universities (such as Keio, Waseda and Tokai) that are also research active, but research activity is concentrated in the national universities. For example, public data show that, in both 1993 and 2002, the top 10 recipients of "Grants-in-Aid" research funding [*kakenhi*] were all national universities, and these 10 alone accounted for about half of the total granted by the Ministry in a given year.[7] Overall, government funding accounted for about 58% of university R&D expenditures in 1981, declining to 49% in 1998, while industry funding increased from 1% to 2.3% in this same period (see Fig. 1) (NSF, 2002).

Compared to the U.S., research in Japan is more concentrated in terms of the distribution across institutions. Tables 2 and 3 show the percent distribution of grants-in-aid/federal funding across the top 10 universities in the U.S. and Japan in 1993 and 2001 or 2002. We see that the top U.S. university, Johns Hopkins, accounts for just under 5% of the total in 2001. In Japan, Tokyo University accounts for about 14% of the 2002 total, about 3 times as much. Similarly, the top 10 American universities, which includes a mix of public and private universities) account for just over 20% of the total each year, while the top 10 Japanese universities (all national universities) account for about half of the total. While we would expect concentration to be somewhat higher in Japan because there are fewer universities overall, we find that, even among the top 10, concentration is greater in Japan. The Gini coefficient for inequality among the top 10 in the U.S. is .17 in 2001, and .19 in 1993. In Japan, the Gini coefficient is .35 in both years. In addition, there is more stability in the rankings in Japan than in the U.S. The correlation of the rankings in the top 10 across the two years is .95 in Japan and .71 in the U.S.

Since the national universities are government agencies, they could not, until recently, independently own patents. Instead, the national government was the

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the creation of the Post Office in the U.S. as an independent government entity in 1971, or a similar change in Japan in 2003). This agencification is expected to produce a variety of changes in the system described, which we will address below.

[7] Similarly, Pechter and Kakinuma (1999) report that of the universities that co-authored with Japanese firms over the period 1981-1996, the top 10 collaborating institutions were all national universities.

institution with ownership rights in university inventions. However, the professors could often become the owners of their own inventions, depending on the source of funding for the research that generated the invention (Kneller, 1999a, Yoshihara and Tamai, 1999). In Japan, funding for university research comes from several major sources. The first is the regular research allowance given to each chair [*kouza*]. Each chair consists of a professor and one or more associate professors and research assistants and is allocated funding based on a standard formula (Yoshihara and Tamai, 1999, Coleman, 1999). This research allowance accounts for about 44% of the total research budget at Japanese national universities (budget percentages are from Kneller, 1999a). This standard formula produces a relative leveling of funding across universities and departments (Coleman, 1999). The second major source of funding is the Grants-in-Aid [*kakenhi*], which accounts for roughly 30% of total funding.[8] These are grants given to fund specific projects and are allocated according to a competitive, peer review system. As we have shown, these grants are concentrated in a few national research universities. This funding generally does not include budget for salaries for faculty or for graduate or postgraduate research assistants, and includes a very small amount for overhead costs (approximately 10%). In the national universities, it is very difficult to hire temporary research personnel on a project basis (Kneller, 1999b). It is also difficult to take a leave of absence to work on funded projects and have one's teaching replaced by adjunct instructors.[9] This reduces the flexibility of the system in responding to changing funding levels in particular labs, because researchers are basically a fixed cost.

Private firms also fund university research. One method is through commissioned research or joint research for specific projects, which together account for about 10% of the total budget. Another is through donations [*shogaku kifukin*]. These donations, which account for about 15% of the total, are often given to support a particular professor's lab, but are not linked to specific projects. These donations form a key component of the system of informal exchanges that link particular firms with

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[8] The actual percent is something below this since non-national universities are included in the total Grants-in-Aid budget (Kneller, 1999).

[9] While professors do get "seconded" to research institutes and other posts, their teaching is covered by their former colleagues, who expect the favor reciprocated on the professor's return.

particular professors (Kneller, 1999b, Hashimoto, 1999, Odagiri, 1999). Professors generally like such donations because they are more flexible than other funding sources, for example, they can be rolled over from one fiscal year to the next and can be allocated to various budget categories (Yoshihara and Tamai, 1999, Kneller, 1999a).

Ownership of professors' inventions depends on the source of funding. Inventions coming from projects that are supported by Grants-in-Aid are owned by the national government, but those supported by the standard allotment or by donations are owned by the professor individually. Those supported by firms for commissioned research may be co-owned by the state and the firm, with the exact distribution of ownership negotiated among the parties involved (Kneller, 1999a). Yoshihara and Tamai (1999) and Kneller (1999a) suggest that these rules contribute to a system where professors strategically allocate inventions to projects, claim individual ownership of their intellectual property, and then pass their inventions to firms informally (generally to the firms that have been making donations), leaving the firms to patent the invention (generally with the professor listed as the inventor). About 90% of invention disclosures end up being assigned to the individual professor (Yoshihara and Tamai, 1999). This system of donations and disclosing to firms creates flexibility and reduces transaction costs, so long as both sides trust and cooperate with each other (which is likely, since this a repeated game). Kneller (1999b) estimates the rate of informal transfers in Japan is about equal to the rate of formal transfers in the U.S., suggesting the system is reasonably successful in moving university inventions into firms.

Thus, although the Japanese system for transferring IP from universities to industry may be formally more centralized than the American system in the sense that university IP is vested in the central government rather than the universities, in practice Japan may be *less* centralized since it is typically the individual professor that controls the IP. Thus, to the extent that technology transfer in Japan involves a transfer of IP, such transfers largely reflect informal exchanges between professors and firms, while, in the U.S., such transfers typically entail some formal, contractual relationship with the university.[10]

[10] In the U.S., negotiating these contracts is often a source of vexation due to the costs and delays (Eisenberg, 2001, Walsh, et al., 2003). In addition, very few of these TTOs generate a profit, although the occasional homerun at one university or another provides hope that a big income is just around the corner (Owen-Smith and Powell, 2001). Also,

One problem with the Japanese system is that, to the extent that the firm does not have clean title to the invention, it cannot ensure exclusivity. However, as Cohen, et al. (2002b) have shown, firms across the entire manufacturing sector in Japan do not typically use their patents to exclude others from using their IP, but tend to use them as bargaining chips to gain access to other firms' technologies. Another limitation of this means of transferring IP from universities to Japanese firms is that it foregoes an "arms-length" market mechanism for allocating inventions, in favor using embedded relationships to share technical information. However, prior work (Uzzi, 1996, Murray and Poolman, 1982 Hansen, 1999) suggests that for complicated technical information, such embedded ties are the most effective way to share information.

An additional form of linking firms to universities is placing researchers in university labs. According to Aoki (1988), this may be an important mechanism for information flows between universities and firms, as well as among firms. University labs act as the mediators for negotiating knowledge transfers, not only by hosting visiting researchers from industry, but also by organizing study groups (*kenkyuukai*) that create networks for information sharing among university and industry researchers (Hashimoto, 1999, Pechter, 2001).[11] Thus, the Japanese institutional context creates a system of multi-plex, informal ties between firms and university professors.

Recent university reforms have relaxed some of the restrictions on commercial activity by national universities and their professors and attempted to formalize some of the transactions between universities and firms. The Technology Transfer Law (1998) allowed the establishment of Technology Licensing Offices (TLOs), independent of, but affiliated with, particular universities. There are currently over 30 TLOs, representing nearly all research universities. University-owned inventions can be licensed through the affiliated TLO. And, professors can voluntarily assign their individually-owned inventions to the TLO, although they are not required to do so. Patent fees for universities were also reduced. In 1997, the restrictions preventing professors from

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even in the U.S., personal linkages between firms and professors are an important component of the transfer process (Owen-Smith and Powell, 2001).

[11] Recent survey data suggests that *kenkyuukai* rank just behind meetings and publications as the mechanism by which firms and universities establish ties that lead to cooperative research (Baba, et al., 2003).

starting businesses, or becoming directors or employees of private firms were relaxed. After 1997, professors could work for companies part-time if the goal is to conduct or guide R&D (Odagiri, 1999). In 2000, the National Public Service Law was amended to allow professors and university researchers to take management positions in university startups and to join Scientific Advisory Boards of for-profit firms. In October, 2002, the authority for approving such outside activities was transferred from the National Personnel Authority to the president of the professor's university. The Japanese Bayh-Dole Act (1999) made it easier for firms to get licenses to inventions originating from state-sponsored research. On April 1, 2004, the national universities will become independent legal entities (so-called "agencification" [*houjinka*]). This agencification may result in significant changes in funding, personnel systems and research priorities. For this discussion, one of the most significant changes will be that agencification will give the universities ownership of faculty inventions, which will make the system of IP ownership closer to that in the U.S. Another policy initiative designed to encourage university-industry linkages was the "Hiranuma Plan", initiated by METI in 2001. This plan included a goal of establishing 1000 university startups in three years (as well as subsidies designed to foster that goal), sending a clear signal to universities. They have responded, with the number of startups increasing from 26 in 1998 to 531 in March of 2003 (Matsumaru, 2003).[12] Universities have also received a variety of subsidies to encourage technology transfer. These changes are in sharp contrast to the period of the 1960s, when student protests targeted university-industry linkages, leaving a legacy of suspicion around such activities that still colors the debates to some extent (cf. Hashimoto, 1999). In fact, this legacy contributes to the perception that industry and university are and should be separate worlds and that universities provide little of use to firms.

Comparing University-Industry Linkages in the U.S. and Japan

Several prior studies have highlighted the growing linkages between universities and firms over the last two decades in both the U.S. and Japan (Narin, et al. 1997,

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[12] While the venture capital sector in Japan may not be as large or as active as in the U.S., it is a growing presence in the economy, and many of these university startups are funded by venture capital.

Cohen, et al., 1998, Branscomb, et al. 1999, Hicks, et al. 2001). However, policy debates frequently begin by pointing to the relatively poor performance of Japanese universities on such indicators as patents, licensing and industry funding (see, for example, Hashimoto, 2003). For example, Figure 1 gives the percent of university research budgets that come from industry. We see that during the 1980s, in each country, there was a substantial increase, with growth leveling off since then. In addition, we see that the percentage is much higher in the U.S. than in Japan, with 1999 figures showing the U.S. at over 7% and Japan at just over 2%.[13] As we can see from Table 1, similar conclusions can be drawn when we compare patenting, university licenses, licensing revenue, etc., all of which are significantly greater in the U.S. than in Japan (Hashimoto, 2003).

However, recent work by Pechter, Odagiri, Hashimoto, Tamai and others all suggests that these measures may be biased in the direction of emphasizing the American strengths. For example, Pechter (2000) shows that industry-university co-authorships are growing in both countries and that they are as strong in Japan as in the U.S. Furthermore, he finds that it is not primarily U.S. universities that are the partners in these collaborations, but that the vast majority of joint publications are co-authored with domestic institutions (cf. Hicks, et al. 2001). Similarly, Hicks (1993) finds substantial university-industry links in Japan and that these links are primarily with domestic, rather than foreign universities.

Yoshihara and Tamai (1999) argue that the differing institutional contexts described above produce substantially different numbers of university-owned patents in each country, making patent counts and licensing counts based on university patenting a poor metric for comparing the influence of university research on industry. To give one example, they report that in 1996, Japanese universities filed 90 patents with the JPO, while faculty at Japanese universities filed 941 applications as individuals that same year. Similarly, in that same year, while University of Tokyo filed only 3 patents, Tokyo's engineering faculty were listed as inventors on approximately 150 patents, over half of which were filed by private companies.

These studies suggest the need for additional sources of data that allow

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[13] However, Pechter provides recomputations of this funding data that suggests that the gap is much smaller (Pechter, 2001).

comparisons that are sensitive to the different institutional contexts in which university-industry linkages are embedded in each country.

3. Method, data, and samples

While many studies have taken advantage of bibliometric data on the outputs of university and firm research, such as publications and patents, to demonstrate university-industry linkages, we suggest that supplementing these indicators with survey data that reflect how firms use the products of public research, and how public research compares to other sources of information, would highlight the role of public research along a broader range of dimensions and may overcome some of the biases associated with the more widely used metrics. In order to answer these questions, we used data from the Carnegie Mellon and NISTEP surveys of Industrial R&D. The data come from a survey of managers of R&D units of manufacturing firms in the US and Japan. Responses were matched to each R&D unit's *focus industry* that represented the bulk of its R&D effort.[14]

Where possible, our surveys employed objective response scales, which tend to be both more interpretable and more readily compared across respondents, which is especially useful for comparisons across nations where language and culture differ. First drafted in English, the questionnaire was translated into Japanese and then independently back-translated into English to assure accuracy. While most questions were identical between the two surveys, a small number of questions differed. The surveys were mailed during the summer of 1994. Both the American and Japanese teams conducted follow-up mailings and phone calls to increase response rates (cf. Dillman, 1978).

The population sampled in the U.S. included all R&D units belonging to R&D performing manufacturing firms located in the U.S. The U.S. sample was drawn from a frame consisting of eligible labs in the Directory of American Research and Technology (Bowker, 1994) or, if not included there, labs attached to firms listed in Standard and Poor's COMPUSTAT tapes. We surveyed 3240 labs located in the U.S. and received

[14] By obtaining answers for a firm's activities and experience in a given product market rather than the firm as a whole, we reduce the measurement error associated with differences in conditions across the several industries in which a firm might be active.

1478 responses, for a raw response rate of 46% and an adjusted response rate of 54% of the eligible sample.[15] The U.S. survey data are supplemented with published data on firm sales and employees from COMPUSTAT, Dun & Bradstreet and similar sources. The population sampled in Japan included R&D performing, manufacturing firms with capitalization over 1 billion yen. The sample was drawn from a list of 1219 firms amassed by Japan's Science and Technology Agency, or 71% of the 1722 firms estimated to meet the population definition (Goto and Nagata, 1997). The data include responses from 643 firms, yielding a response rate of 52%. In order to make the two national samples as comparable as possible, we restricted our samples to respondents from firms with annual sales of US$50 million or more.[16] Foreign-owned labs were also dropped in order not to confuse our cross-national comparisons.

In this truncated sample, there are 826 observations from the US and 593 from Japan. Because the two national samples can contain very different numbers of observations for a given industry, we constructed weights that correct for the differences in industry mix in each country, and use these weights when comparing national aggregate results in order to rule out the possibility that country differences are due to variations in industry mix. Furthermore, we weighted the averages by the log of business unit R&D employees, in order to better represent the overall country averages.[17] When we make comparisons between these country averages, we use weighted logistic regressions. For comparisons across survey item averages within a country, we use paired *t*-tests or non-parametric tests (Agresti and Agresti, 1979).

Presenting summary statistics on firm and business unit sizes for the two samples, Table 4 shows that the U.S. sample contains substantially larger firms, though the business units (reflecting firms' activities in a given market) are more comparable in size. Consistent with public sources, our data indicate that Japanese firms spend more

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[15] A nonrespondent survey found that 28% of the nonrespondents in the US were not in the target population (for example, they did no manufacturing). After correcting the sample size accordingly for ineligible cases, the US response rate was adjusted upward to 54%.

[16] An analysis of the full sample from the U.S. survey provides results that are qualitatively similar to those provided here (see Cohen, Nelson and Walsh, 2002a).

[17] Because our samples contain some very large firms, these outliers overwhelm a simple weighted average. Using the log of business unit R&D employees as the weight provides a balance between the need to give the larger firms more impact on the national averages and the need to reduce the impact of extreme values.

on R&D relative to sales than comparable U.S. firms. For our sample, the comparison means for own-financed business unit R&D expenditures divided by worldwide sales are 2.26% for the U.S. and 3.70% for Japan (t = 6.89, P <0.0001).[18] Our survey data suggest that the overall Japanese sample R&D intensity exceeds that of the U.S. largely because, in industries that are low on R&D intensity (i.e.,<2% in the U.S.), the Japanese R&D intensities tend to be considerably higher. In contrast, in the most R&D intensive industries such as drugs or semiconductors, the average U.S. and Japanese R&D intensities tend to be comparable.[19]

4. Measuring the impact of public research on industrial R&D

We begin by estimating the relative effects of public research on industrial R&D in each country. Our surveys provide several measures of the impact of universities and public research institutions on industrial research and development. We focus on the following measures: whether public research suggested new projects and/or contributed to project completion; how frequently firms receive useful technical information from domestic public research institutions and those overseas; and what percent of R&D projects make use of public research.

First, we asked firms whether public suggested new projects over the last three years. We also asked if public research contributed to the completion of existing projects over the last three years.[20] For these two items, we also asked the same question with respect to several other potential sources of information, including customers, competitors, the firm's own manufacturing operations, affiliated suppliers, independent suppliers, etc. These items allow us to test the relative importance of

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[18] Our sample data excludes outliers, defined as business units with R&D intensities >100% or more than three interquartile ranges from the median.

[19] Public data show that over the last 10 years, Japan has consistently spent more on R&D as a percent of GDP than has the US. Over the last 5 years, the Japanese average has been between 2.77 and 3.01%. During this same period, the US average has been between 2.48 and 2.63% (National Science Foundation, 2002). If we include only non-defense R&D, the gap is even larger. We believe our aggregate results exceed the public data largely because we sampled only R&D-performing firms.

[20] In the U.S., we asked about universities and government research labs. In Japan, we had two items, one for universities and one for government research labs. We combined these into a single measure, with respondents who gave a "yes" response to either item coded as "yes" on this measure.

public research compared to other sources of information. The results are in the top rows of Figure 3. The dark bars represent the Japan respondents and the light bars are those from the U.S. The first item is the (weighted) percent of respondents who report that public research suggested new projects. Over half of the firms in Japan said "yes" to this item, and about 40% of American firms also said that public research suggested projects. In terms of project completion, 53% of Japanese firms and 46% of U.S. firms report that public research contributed to the completion of existing projects.

Comparing these summary statistics suggests two conclusions. First, the Japanese firms score higher than the American firms on both items ($p<.0001$). Second, public research is at least as important for helping to complete projects as it is for suggesting new projects. This result suggests that relationship between public research and industrial R&D in Japan, as in the U.S., appears to reflect a feedback model.

If we compare public research with other information sources on these measures (Figures 5 and 6, discussed below), we find that for the U.S., public research ranks below customers, manufacturing or suppliers, but about the same as competitors, in terms of suggesting new projects (Cohen, et al, 2002a). In terms of its contribution to project completion, public research again ranks below information from customers, own manufacturing and suppliers, but rank above competitors. For suggesting new projects to Japanese firms, public research ranks below customers (the most important source in both countries), but about the same as own manufacturing and competitors and ahead of suppliers. For contributing to project completion, Japanese firms rank public research below customers and manufacturing, about the same as competitors and ahead of suppliers. Thus, in both countries, we find that public research is not as important as customers as a source of information, nor, generally, as important as a firm's own manufacturing unit or (in the U.S.) its suppliers. However, it is approximately as important as competitors as a source of information (and more important than suppliers in Japan). Since prior work has shown that "intraindustry R&D spillovers," roughly equivalent to our notion of information from competitors, contributed significantly to technical advance and productivity growth within industries (Bernstein and Nadiri, 1989, Griliches, 1992), one might infer that public research also makes a significant contribution to industrial R&D.

To probe further the relation between public research and industrial R&D, we asked firms how frequently they received useful technical information from public research institutions in their own country, and also in the other country (i.e., we asked U.S. firms about Japan and Japanese firms about the U.S.). This item allows us to consider whether national proximity affects the employment of the public research, or whether, for example, it is mainly American public research that contributes to technical advance in both Japan and the U.S. To summarize these data, we calculate the percent of respondents who report receiving information at least monthly. The middle part of Figure 3 gives the summary statistics. In Japan, almost half of respondents report receiving useful technical information at least once a month from domestic (i.e., Japanese) universities and government research institutions. The analogous U.S. figure is about 39% (country difference significant, $p<.0001$). In terms of receiving information from public research institutions in the other country, about 16% of Japanese firms report receiving information at least monthly from American institutions, while 7% of American firms report receiving information at least monthly from Japanese institutions (country difference significant, $p<.0001$). Thus, we can see that it is primarily domestic universities and public research institutions that are the key source of technical information (domestic-overseas comparison significant, $p<.0001$). In particular, while Japanese firms rely more on American institutions than American firms rely on Japanese institutions, Japanese firms rely even more heavily on Japanese institutions (cf. Iwasa and Odagiri, 2002). These results echo Pechter's findings that Japanese firms collaborate primarily with Japanese universities. Narin et al. (1997) also find that, among a set of U.S. patents, firms cite papers originating predominantly from their home country institutions. Japanese patents cite Japanese universities about 4 times more than they cite American universities, although they also cite American papers at a rate slightly above 1.0.[21]

Finally, we asked firms what percent of their R&D projects make use of public research. Here, we find little difference between countries, with both reporting a little under 20% of projects. We also asked what percent of projects made use of prototypes or of new instruments and techniques (not shown). For prototypes, the percentages were 5% in the U.S. and 7% in Japan. New instruments and techniques were used by 12% of projects in each country. These results, which put a numeric estimate on the

[21] Interestingly, Japanese publications are also overcited by French and Germany patenters (although undercited by American patenters).

impact, suggest that in both countries, public research provides useful information for a significant fraction of industrial research. On these measures, we find Japan scores about the same as the U.S.

5. What Fields Have the Most Impact on Industrial R&D?

Building on the work of the earlier Yale survey (Klevorick, et al., 1995) and our analysis of the U.S. data (Cohen, et al., 2002a), we examined firms' evaluations, by field, of the importance to their R&D (using a four-point Likert scale) of public research conducted over the last 10 years for each of ten fields: biology, chemistry, physics, mathematics, medical and health science, materials science, chemical engineering, electrical engineering, mechanical engineering and computer science.

To summarize the data, we calculated the percent of respondents in an industry who report that a given field was at least moderately important ("3" or greater on the four point scale). We then examine these summary data to identify, for each industry, the fields where at least half of the respondents in a country report the field to be at least moderately important. To begin, we find that the most generally useful field is materials science. For the U.S. sample, in 16 of the 29 industries, at least half of respondents report the field of materials science to be at least moderately important for their R&D. In Japan, the figure is 18 of 29 industries. Thus, to the extent there is a "general purpose" field of public research that is linked to industrial R&D, materials science fits that description. Chemistry is also widely applicable, with 13 industries in the U.S. and 12 in Japan showing chemistry as being at least moderately important for the majority of firms. Beyond these two fields, we find that the other fields are more narrowly applicable, in somewhat expected ways. For example, in both countries, biology is important for the drug industry, with 72% in the U.S and 83% in Japan scoring biology at least moderately important. The applied fields are somewhat more broadly applicable, replicating the findings from Klevorick, et al. (1995).

To further estimate the overall impact of public research on industrial R&D, we calculated the number of industries for which at least one field is relevant to the majority of firms. Using this measure, we can see how widespread the effects of public research are. In the U.S. 25 of 29 industries report at least one field being moderately important for the majority of firms. For Japan, the figure is 28 of 29, again suggesting that public research has at least as great an impact in Japan.

6. Accessing Public Research

Next we address the mechanisms by which firms gain access to public research results. We asked our respondents the importance to a recently completed "major" R&D project of each of 10 possible sources (or channels) of information on the R&D activities of universities or government R&D labs or institutes. The information sources considered include patents, publications and reports, informal information exchange, public meetings and conferences, recently hired graduates, licenses, joint or cooperative ventures, contract research, consulting, and temporary personnel exchanges.

Figure 4 shows the percent of respondents in each country that rate a given source as moderately important or higher ("3" or more on the four point scale). We can see that the two most important sources are publications and meetings. These "public" sources were emphasized by about 40% of the American respondents, and about three-quarters of Japanese respondents. In the U.S., consulting and informal interaction also score high (about 40% saying these are at least moderately important). In Japan, patents, informal interaction, and contract research score high, with over half highlighting these mechanisms.

The high score of patents in Japan deserves some comment. Prior research using these same surveys shows that for Japanese industrial researchers, patents are the most important source of technical information on rivals' R&D (Cohen, et al., 2002b). Also, as noted above, while universities own relatively few patents in Japan compared to the U.S., professors at Japanese universities are frequently identified as the inventors on patents that are applied for by firms, and these patents may be seen as a source of information about public research. For Japanese industrial researchers, patent documents are treated like a useful, widely read journal. Firms' engineers regularly comb through the patent publications looking for usable information, and hence will find university-based inventions through this channel, much as they would from reading journal articles. Thus, it is not surprising that patents score highly in Japan as an important source of information about public, as well as industrial, research findings.

In terms of country differences, nearly all mechanisms overall score more highly in Japan than in the U.S. (country differences significant, $p<.05$ or smaller). The exceptions are recently hired technical personnel and consulting. The first is consistent with the lower lateral mobility in Japan compared to the U.S., related to the so-called life-time employment system (which has been weakening lately). The second is not surprising, as professors at the national universities (which account for the bulk of research) were, until recently, quite constrained in their ability to consult.[22] But, even with these constraints, Japanese firms rate university and government research, particularly that which flows through the channels of open science (such as publications and conferences), as more important than do American firms, again suggesting that the linkages are at least as strong in Japan as they are in the U.S.

If we now turn to more formal linkages, we find that in both countries, licenses score quite low as a mechanism for transmitting information from public research institutions. In the U.S., only 10% of respondents report that licenses are at least

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[22] As noted above, professors in the national universities were severely restricted in their ability to do paid consulting until fairly recently (Nishizawa, 2002). And, even unpaid consulting was limited in terms of hours per week (basically, outside the scheduled work week). The following Q&A on the MEXT web page highlights these restrictions.

Q&A on Partnership Between Universities and Industry
Q: Is it possible to receive regular technical guidance from Professors?
A: You can receive technical guidance and counseling on research and development from university professors at certain period. In this regard however, Please note the following:
1.Consultation is limited to non-working hours of the professor and must not interfere with the professor's normal duties.
2.Professors must go through a screening committee, and obtain approval for being involved in another line of work.
3.Remuneration is restricted to a socially acceptable level.

Q: I would like to provide some form of remuneration to the professor who helped us.
A. Since a professor is conducting research in a university, a form of civil service, it is unnecessary to show appreciation individually (allowance for the service, etc.).
Any professor who is a public official and accepts the allowance or gifts for work from any organization other than the central government may be liable to prosecution for corruption and bribery, along with the party which made said provision of money or gifts.
However, there is no particular problem with 1. profit made by the individual professor from selling properties (e.g., a patent attributed to the individual professor approved by an Invention Committee), 2. fees for publication and lectures, and 3. remuneration in cases where the individual has permission to be involved in another line of work. Furthermore, a program for Grants and Endowments is in place for donations to education and research and national universities. It is also possible to provide contributions to particular professors and research, but these must be received and expensed through the central government's accounting system.

(http://www.mext.go.jp/english/news/2000/04/s000450f.htm [typographical errors corrected]) moderately important, second from the bottom and ahead of only personnel exchanges. In Japan, 28% of firms report licenses as useful, ahead of only personnel exchanges and recent hires. In addition, in the U.S., the next least popular source is patents, with only 20% scoring patents as at least moderately important. Patents do better in Japan, for the reasons suggested above. These results suggest that the "archetypical" technology transfer model in the U.S., of a university patenting a professor's invention and then licensing it to a firm, may be much less central in the university-industry relationship than the more conventional methods of disseminating university research results, such as papers, meetings, and personal contact between researchers (see also Agrawal and Henderson, 2002).[23]

7. Industry Differences in the Importance of Public Research

In addition to comparing overall means across countries, we also looked at industry by industry scores to see which industries scored particularly high in terms of the impact of public research, and whether this varied by country.

Our main finding is that, in both countries, the drug industry stands out as the most closely linked to public research. To consider the industry-by industry effects, we considered all of our impact variables, including the degree to which public research suggests new projects, contributes to project completion, firms use findings from domestic as well as other national public research institutions, percent of R&D projects using public research, and "maxsci" (the highest relevance score across eleven fields of science and engineering). Across all our measures, the drug industry was in the top quartile of industries in both countries, and scored either first or second on two of these

[23] Of course, the low score of licenses and (in the U.S.) patents may be due to firms making a distinction between the channels of information flow and the importance of these sources for acquiring the technology (though licenses). However, we believe that this item may be a useful measure of the overall impact of licenses, not just their informational value. One piece of evidence supporting this interpretation is the very high score for licenses and patents in the drug industry in both countries. In the drug industry in the U.S., 70% of respondents report patents to be at least moderately important (industry difference significant, $p<.0001$). Similarly, 42% of American respondents report that licenses are at least moderately important (industry difference significant, $p<.0001$). Japanese drug firms also report high scores for patents (83%) and licenses (71%).

in the US (contact with domestic public research institutions and maxsci) and all six in Japan. Beyond the drug industry, we also looked at other industries that consistently ranked in the top quartile of industries in each country. For the U.S. we found that communications equipment scored in the top quartile on five of our measures. Car/truck and petroleum ranked highly on four measures, while semiconductors and mineral products ranked in the top quartile on three of the measures. For Japan, medical equipment ranked in the top quartile on all six items. Semiconductors; motors/generators; computers; concrete, cement, ceramics; and chemicals (nec) each ranked in the top quartile on three measures. While high-tech industries such as drugs and semiconductors appear to be closely tied to public research in each country, we also find mature industries such as automobiles and motors/generators among those most dependent on public research.

We also examined industry by industry exceptions in the overall pattern of Japanese firms rating universities at least as highly as did American firms. Using our five measures from Figure 2, we compared industry by industry across the two countries. The first finding is that, in contrast to our earlier research on information spillovers in the Japan and the U.S. where we found that the greater inter-firm spillovers overall in Japan were largely replicated in the industry-by-industry comparison (Cohen, et al., 2002b), in the case of university-industry links, we find much more variation in which country ranks on top in the industry-by-industry comparisons. Of the 29 industries, the U.S. is greater than Japan in three industries for suggest new projects, ten for contributing to project completion, ten for frequency of contact with domestic universities, eight for the other country's universities, and twelve for percent of projects using public research. The industries where the U.S. firms seem to have significantly stronger ties than the Japanese are communications equipment (where the U.S. is higher on all five measures, including frequency of contact with the other country's public research) and car/truck (where the U.S. is higher on all but frequency of contact with the other country). In addition, we see that in both drugs and medical equipment, Japanese firms rate public research substantially higher than do American firms. Furthermore, in these two industries, frequency of contact with American universities is substantially above the Japan average, suggesting that these are industries that are drawing most heavily on American research (as well as drawing well above average on Japanese public research). In computers, Japanese firms also seem significantly closer to public research than are American firms, and again, are drawing heavily on American (as well as domestic) public research.

8. Explaining the gap: Why do Japanese firms make greater use of public research?

Our simple descriptive results suggest that Japanese firms make at least as great, if not greater, use of public research as American firms, although in some industries, the pattern in reversed. Indeed, we find that, for four of our five measures of impact (see discussion above and Figure 3), Japanese firms appear to make greater use of public research than American firms. Recall that the aggregate descriptive findings were computed with R&D weights. If these weights are dropped, and we compute unweighted simple averages, the difference in favor of greater intensity of use of public research among Japanese firms increases, and, for the one measure (% of R&D projects) where U.S. firms came out ahead with the weighted data, the Japanese firms now appear to dominate slightly. Moreover, if we run a logit (or ordered logit) for our key three measures (see Tables 6a through 6c, discussed below) and control for firm size, we find the coefficient on a dummy variable representing Japanese firms to be positive and significant, suggesting that Japanese firms make significantly greater use of public research than U.S. firms

Building on prior work on the factors associated with stronger university-industry linkages (Santoro and Gopalakrishnan, 2001) and on country differences in firm organization (Lynn, 2002, Clark, Chew and Fujimoto, 1987), we provide some preliminary results on the question of what organizational and institutional factors might explain the stronger links between firms and public research in Japan.

One possible explanation is that Japanese firms are simply more aggressive about accessing outside information from any source. While this theory has some supporters (see Lynn, 2002, for review), our data suggest that this is not the case. As reported in Cohen, et al. (2002b), Japanese R&D personnel do not spend substantially more time monitoring extramural technical information (12.2% of R&D employees' time in Japan versus 11.7% in the U.S.), nor do they spend more on advanced training of their R&D personnel (6.9% in Japan versus 8.3% in the U.S.). In addition, while Japanese firms obtain more information from rivals and from public research, they do not uniformly report greater access to extramural sources. Figures 5 and 6 give the country averages across a variety of sources of information, including firms' own manufacturing units, customers, independent suppliers, joint ventures, consultants, as well as competitors and public research. In terms of suggesting new projects, Japanese firms do make greater use of competitors and public research. However, American firms report greater use of customers, their own manufacturing units, joint ventures, independent suppliers and consultants. In terms of contributing to project completion, Japanese firms make greater use of customers, public research, and competitors, while American firms make greater use of consultants, joint ventures, independent suppliers, and their own manufacturing units. Thus, there is no consistent pattern of country differences across information sources. Thus, we reject the hypothesis that it is a general propensity to access outside information that explains the country differences in use of information from public research. We therefore probe other factors that might explain the difference.

Based on surveys of Engineering Research Centers and other university-industry cooperative research centers in the U.S., and their partner firms, Santoro and Gopalakrishnan (2001) find several factors that are associated with stronger university-industry ties. These include trust, geographic proximity, and flexibility of university IPR policies. These findings suggest that one explanation for the observed country differences is that Japanese firms are, on average, better positioned with respect to these factors. For example, it is likely that industrial engineers are, on average, geographically closer to the site of public, and especially university research in Japan than in the U.S. Japan's two main metropolitan areas, Kanto (Tokyo-Yokohama) and Kansai (Osaka-Kyoto) contain 5 of the top 10 research universities, account for over 30% of total funded research. These two cities are also where the bulk of Japan's industrial R&D labs are located. In contrast, in 1993, only one state in the U.S. contains more than one of the top 10 research universities, and that state, California, is about the same size as all of Japan, while its four major research universities accounted for less than 8% of total university R&D.

Another possible explanation for these differences is that industrial engineers in Japan are better positioned to take advantage of a broader range of public research results because of their more general training. Lynn (2002) reviews the literature on organizational differences in engineering in Japan and the U.S. and finds that one important difference is that Japanese engineers have broader and more general training (cf. Clark, Chew and Fujimoto, 1987). Regular job rotation is one important contributor to this training (see also Shapira, 1995). One type of rotation is placing mid-career engineers in a university lab, which is primarily designed to give the engineer exposure to current research results and techniques, in addition to executing a particular research project (Aoki, 1988). Another interpretation of these same practices is that they produce engineers that are more generalist and hence more dependent on universities for technical knowledge than are their more specialized American counterparts.

U.S. and Japanese firms may also differ in the extent to which they engage in basic research. Basic research may contribute to absorptive capacity permitting more effective consumption of public research (Cohen and Levinthal, 1989). Firms' basic research may also more easily be integrated with public research, allowing joint research, or at least shared conversations about related research.

Our survey provides several items measuring the various organizational characteristics and practices designed to facilitate information flows to the R&D lab (see Table 5). To the extent that basic research augments a firm's absorptive capacity (Cohen and Levinthal, 1989), especially with respect to the less applied research that originates from public research institutions, Japanese firms may well have higher absorptive capacity. During our sample period, we find that Japanese firms engage in more basic research (8.5% of R&D) than do American firms (5.2%).[24] We also find that American engineers are more likely to have training in the academic field that is most closely allied with their current R&D unit's research focus. We interpret this as a measure of how specialized engineers are in a firm. On average, 44% of R&D personnel in an American firm are trained in this "most important field", while only 26% of Japanese come from this field. Similarly, like earlier studies (Shapira, 1995), we find that job rotation is much more common in Japan (75% of firms) than in the U.S. (60%), further suggesting that Japanese engineers are more broadly trained.[25] It is not clear

[24] National R&D statistics from the time of the survey show a similar country difference, with Japan reporting 7% industrial research devoted to basic research and the U.S. reporting 4% (NISTEP, 1995)

[25] However, Shapira (1995) notes that American engineers have broader experience, on average, than do Japanese engineers, in part because Americans are more likely to have

whether greater specialization would increase the impact of public research (because of greater familiarity with the outputs of, for example, university researchers in that specialty), or would decrease the impact, if, for example, engineers need to be able to integrate information from a variety of sources in order to successfully incorporate public research findings into their current projects. As a measure of proximity, we collected data on R&D expenditures, by field and by region (state in the U.S., prefecture in Japan). We then used our estimates of the importance of various fields for the labs' research to weight the field level data and come up with an index of local university research in "relevant" fields.[26] We also have a measure of time spent in monitoring and information gathering, which can be seen as another measure of investment in absorptive capacity.[27]

As noted above, we also have a measure of the channels through which firms access university research. We focus on four channels.[28] Since publications and reports are a key output of universities and government research institutions, the most important channel for accessing public research (see above), and less geographically constrained than other mechanisms, we included reliance on publications as one channel, which we can think of representing "public science".[29] We also include accessing public research through informal interaction, in part because we suspect that Japanese firms may have closer ties to professors, for example, through study groups (*kenkyuukai)*, or more generally, due to greater proximity. We also include contract

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worked at other functions at a different firm.

26 For the U.S., we used NSF data on R&D expenditures at universities and colleges, by state and by field (engineering, physical sciences, math and computer sciences, and life sciences). For Japan, we used grants-in-aid funding (*kakanhi*) by prefecture and by field. Because *kakenhi* represents about 30% of total university research budgets (Kneller, 1999), we multiplied these totals by 3.33. We then assign these field-level expenditures to respondents according to location. To create the index, we weighted the field-level expenditures for the respondent's location by the scores on our survey items measuring the importance of a field of science or engineering for a firm's R&D.

27 However, because the incentive to invest in such activity may be conditioned by the utility of external, in particular university-based, sources of information, we recognize that this variable may be endogenous.

28 These channels were chosen partially based on the literature cited above and partially based on a specification search designed to identify the mechanisms that were strongly associated with the use of public research.

29 When we used "public conferences and meetings" as our measure of public science, we obtain very similar results. These two items are correlated about .70 in each country.

research, a formal tie, in part as a contrast with more informal mechanisms. Finally, we include temporary personnel exchanges as a channel, as prior research on R&D management in Japan suggests that this may be a key country difference in the means for accessing university research (e.g., Aoki, 1988). All four of these channels score higher in Japan than in the U.S. (see Table 5).

Although we do not have direct measures of trust, or flexibility of IPR policies, we do have reasons to believe that these are greater in Japan, and that this might contribute to the observed country differences. Since relationships tend to grow in trust over time, the relatively longer tenure of Japanese engineers with their companies (compared to American engineers) should increase the trust between the personnel of a given company and university faculty (Lynn, 2002). Finally, while American universities may have more freedom to set formal IPR policies, we have already noted that informal transfer of intellectual property, while present in the U.S. (Owen-Smith and Powell, 2001), is the norm in the Japan (Kneller, 1999b). Thus, we suspect that this greater ability to informally receive university-based IPR may also contribute to the observed difference in use of public research. While we did not measure the flexibility of university IPR policies directly, we do measure the importance of informal interaction as a mechanism for accessing public research results. Again, we see that Japanese firms rate this much more highly than do American firms (Figure 4).

In order to consider whether these organizational and institutional characteristics explain the observed country-level differences, we ran a series of logit (or ordered-logit) regression models with our three key measures of the importance of public research (whether public research institutions suggested new projects; whether they contributed to project completion; and the percent of industrial R&D projects that used public research) as the three dependent variables, and measures of firm characteristics and strategies as the predictors. Insofar as many of our right hand side measures are likely endogenous (some more than others), this exercise should be considered exploratory, providing a first-cut description of a range of empirical relationships.

The results are presented in Tables 6a-6c. For each of the three dependent variables, we first show a baseline model with country, firm size (and R&D unit size for the first two measures) and industry fixed effects (28 industry dummies, not shown).[30]

[30]We include unit R&D employees on the right hand for the two specifications where

We can see that Japanese firms report stronger ties to public research across all three dependent variables. We also see that larger firms report closer links (although the effect for suggesting new projects is not significant), consistent with the results from Cohen et al. [2002a], suggesting that larger firms benefit disproportionately from public research. And, as expected, the number of R&D employees in a unit significantly influences whether public research either suggests new projects or contributes to project completion.

We then add percent basic research, both reflecting a firm's closeness to upstream research and as a measure of absorptive capacity. For all three dependent variables, there is a positive effect (although not significant for contributing to project completion). However, although Japanese firms are higher on basic research, this does not substantially reduce the country difference. We then add specialization (a measure of the percent of R&D personnel receiving their degree in that field for which the plurality of lab personnel received a degree), job rotation (i.e., whether job rotation had been used some time in the prior three years to increase the interaction between the respondent's R&D personnel and other functional units) and proximity. All three are positive, and the effects are generally significant (or nearly so), except for specialization on "suggesting new projects." Including these measures does not reduce the country effect. In fact, the size of the Japan effect increases by about a standard deviation. We then include monitoring (i.e., the percent of R&D personnel time devoted to monitoring and gathering information on new scientific and technical developments). Investment in information gathering and monitoring is associated with public research suggesting new projects and with percent of projects using public research, but not with public research contributing to project completion. The country effect does not change, which may not be surprising since there was little difference between countries in the

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the dependent variables reflect, respectively, whether information from public research has suggested a new R&D project or contributed to the completion of an existing project. This is intended to provide a proxy measure of the number of R&D projects to control for the fact that, as the number of R&D projects increase, it is more likely that information from public research institutions (or any source) will be employed simply on a stochastic basis, not reflecting greater intensity of use of public research. We recognize, however, that R&D unit employees is likely endogenous in these two specifications, and we will instrument for it in the next version of the paper. For Table 6c, this control is not necessary because the dependent variable is expressed as the *percentage* of R&D projects making use of public research.

percentage of R&D personnel time dedicated to monitoring. Adding this variable reduces somewhat the effects of specialization, rotation and local university research.

Finally, we add our measures of the importance of different channels of accessing public research, where we asked respondents to assess, on a semantic Likert scale, the importance of each channel or source of information on public research to a recently completed major project. Of the various regressors in our model, these measures are most clearly endogenous in that firms may well have invested in the use of these different channels in order to access public research. Thus, the perceived relevance of public research may drive the reliance on a particular channel. Yet, what we are trying to do here is examine the degree to which patterns in use of these channels can, in essence, knock out the positive country effect reflected in the significant Japan dummy variable. Of the four mechanisms, contract research generally has the biggest effect (although it is second to publications for predicting percent of projects). Our publications variable also has a positive effect on all three measures. Informal interaction is also generally positive, though only strongly significant in the case of percent of projects. Personnel exchange is only significant in the case of percent of projects. When we include these variables, we find the country effect substantially decreases, becoming insignificant for contributing to completion, and even negative in the case of percent of projects. Thus, when we add measures of the channels of accessing public research (all four of which score higher in Japan), the country differences are largely eliminated.[31] While providing some insight into the sources of the country effect, that insight is, however, limited; the finding simply pushes the question back one level. We still do not know, for example, why Japanese firms appear to more intensively exploit publications, informal information exchange or contracts as links to public research.

In addition to the effects of these differences in organizational characteristics, there are likely to be other, unmeasured factors that explain the observed country differences, and perhaps even provide some understanding of why Japanese firms exploit specific channels more intensively. One possibility is that, during our sample

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[31] To further explore the country differences, we tested several models that included country interaction terms. Overall these analyses provided no evidence of systematic country interaction effects.

period, Japanese universities produce more downstream research, which is more accessible and more useful to firms. For example, American universities produce proportionately more science PhDs, while Japanese universities produce more engineering PhDs. For every 100 engineering PhDs, American universities graduate 191 science PhDs, while the Japanese produce only 49 (NISTEP, 1995). Similarly, only 33% of Japanese university research is "basic", while American university research is 62% basic (NISTEP, 1995).[32] Thus, it may be differences in universities, rather than differences within firms, that explain the country differences.

9. Conclusion

Our prior work showed that, in the U.S., public research was broadly useful for industrial R&D, and that, consistent with a feedback model, it was at least as important for helping complete existing projects as for suggesting new projects (Cohen, et al., 2002a). In addition, we found that open channels of scientific communication (such as publications and conferences) were key for accessing public research. In this paper, we show that, despite a very different institutional context, these results generalize to the case of Japan. Again, we find that public research is about on par with competitors as an information source, suggesting that public research institutions in both countries make a substantial contribution to the progress of technology. Public research is most critical for the drug industry (see Henderson, et al., 1999, Zucker, et al., 1997). However, public research is broadly useful, and the use is not limited to high-tech industries. In addition to industries such as drugs, semiconductors and communication equipment, several mature industries, such as food, motors/generators and car/truck, also depend heavily on public research findings.

Furthermore, in contrast to some (though not all) prior work, we find that the impact of public research in Japan is at least as strong—and perhaps stronger—than in the U.S. Although survey-based, all of our measures of impact point to this pattern. At least part of the discrepancy between studies may reflect the use of different metrics. Studies that rely heavily on either patenting or licensing activity will tend to

[32] Another possible differences is that, because many university professors in Japan are (national) public employees, they may feel a strong obligation to accommodate requests for information from firms (see fn. 22 above). While many professors in the U.S. are state employees, the public servant ethos may not be as strong.

underestimate the strength of ties between public research and industry in Japan, per the discussion above of the different ways in which patents are assigned to the outputs of public research, and because patenting and licensing activity tends to apply differentially across fields and industries. Even in the U.S., patents and licenses are only a small subset of the links between public research institutions and firms (Cohen, et al., 2002a, Agrawal and Henderson, 2002). However, despite this overall pattern, we also see significant differences by industry. In particular, in communications equipment and car/truck, the pattern is reversed, with American firms relying more heavily on public research.

We also made some preliminary efforts to explain the country differences by examining the organizational characteristics that might be associated with links to public research. We find that basic research, disciplinary specialization of the R&D lab, job rotation, proximity to universities, and investment in monitoring technical developments are all generally associated with greater use of public research. However, none of these factors explain the country difference. The use of contract research, publications and informal interaction to access public research are also, not surprisingly, associated with greater reliance on public research. When we control for these different channels, which are all used more heavily in Japan, the country difference is largely eliminated. We noted, however, this elimination of the country effect simply puts the question back one step—why do Japanese firms appears to exploit these channels of access to public research more intensively? A more systematic effort is still needed to measure more clearly the relevant variables and to address issues of endogeneity. Our results, combined with an earlier finding of greater intra-industry spillovers in Japan than in the U.S. (cf. Cohen, et al., 2002b), suggests a need for future research that addresses the factors that drive differences in firms' "realized technological opportunities" across nations—specifically the differences in incentives and abilities to incorporate research from public research and rivals.

Because these data were collected in 1994, they have some weaknesses and strengths that should be noted. Since 1994, much has changed in each country, so that the results might not generalize to contemporary circumstances. However, this also offers us the opportunity to compare the two countries before many of the reforms in Japan, but after many of the American reforms had become institutionalized.

These findings suggest caution when interpreting the relative influence of public research based on indicators that reflect the patent-license-venture model of technology transfer, particularly in the period before reform in Japan. As Japan is currently undergoing substantial revision to its system of national universities (e.g., agencification), we will need to revisit these questions to see how universities are responding to the new environment. Similarly, in the U.S. case, 20 years of experience with the post-reform environment has provided an opportunity for rethinking the relation between public and private research (cf., Nelson, 2001). We should take this opportunity to reconsider what kind of system will achieve the goals of promoting innovation and encouraging economic growth in each country.

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Table 1. Comparison between Japanese and U.S. Industry-University Cooperation

	Japan	US
TLOs	26	142
Patent Applications Filed [1]	1145	5263
Licenses [2]	231	3606
Royalties	$3.0 Million	$1.11 Billion
University-based venture companies	263	2624
Licensing rate [2/1]	17%	64

Source: Hashimoto, 2003.

Table 2. Top 10 American Universities, Federal Funding, 1993, 2001

	1993 USA (Federal R&D)	Percent of total	Cumulative%	2001 USA (Federal R&D)	Percent of total	Cumulative%
1	**Johns Hopkins**	**5.63%**	**5.63%**	**Johns Hopkins**	**4.58%**	**4.58%**
2	U Washington	2.25%	7.88%	U of Washington	2.27%	6.85%
3	MIT	2.24%	10.12%	Michigan	2.06%	8.92%
4	Stanford	2.13%	12.25%	Stanford	2.00%	10.92%
5	Michigan	2.09%	14.34%	Pennsylvania	1.83%	12.75%
6	UCSD	2.03%	16.37%	UCSD	1.79%	14.54%
7	Wisconsin	1.79%	18.16%	Columbia	1.65%	16.20%
8	UCSF	1.76%	19.92%	UCLA	1.63%	17.83%
9	Cornell	1.63%	21.55%	Colorado	1.61%	19.43%
10	UCLA	1.58%	**23.13%**	MIT	1.59%	**21.02%**

r93,01=.71
Gini93=.19
Gini01=.17

Table 3. Top 10 Japanese Universities, Grants-in-Aid, 1993, 2002

	1993 Japan (Kakenhi)	Percent of total	Cumulative%	2002 Japan (Kakenhi)	Percent of total	Cumulative%
1	**Tokyo**	**14.52%**	**14.52%**	**Tokyo**	**14.00%**	**14.00%**
2	Kyoto	9.39%	23.91%	Kyoto	7.12%	21.12%
3	Osaka	6.27%	30.18%	Osaka	5.40%	26.52%
4	Tohoku	5.00%	35.18%	Tohoku	5.20%	31.73%
5	Nagoya	3.92%	39.10%	Nagoya	4.09%	35.82%
6	Tokyo Kogyo	3.69%	42.79%	Hokkaido	3.57%	39.39%
7	Kyushu	3.63%	46.42%	Kyushu	3.40%	42.79%
8	Hokkaido	3.40%	49.82%	Tokyo Kogyo	2.75%	45.54%
9	Tsukuba	1.80%	51.62%	Tsukuba	1.84%	47.39%
10	Hiroshima	1.58%	**53.20%**	Hiroshima	1.55%	**48.94%**

r93,01=.95
Gini93=.35
Gini01=.35

Figure 1. Industry Funded Research as a percent of total academic R&D, US and Japan, 1981 to 1999.

Table 4. Firm and business unit size in the US and Japanese samples.

	Sales (US$Millions)		Employees	
	US	Japan	US	Japan
Firm Size				
Median	145	558	8600	1476
Mean (unweighted)	6067	1956	30009	3720
Mean (weighted)	6020	1793	29272	3462
Business unit size				
Median	300	361	1000	850
Mean (unweighted)	2403	1264	6282	2229
Mean (weighted)	2813	1122	6791	1945

Note: 1USD=103.8JPY, March, 1994 exchange rate.

Figure 3. The impact of university research on industrial research projects in the U.S. and Japan

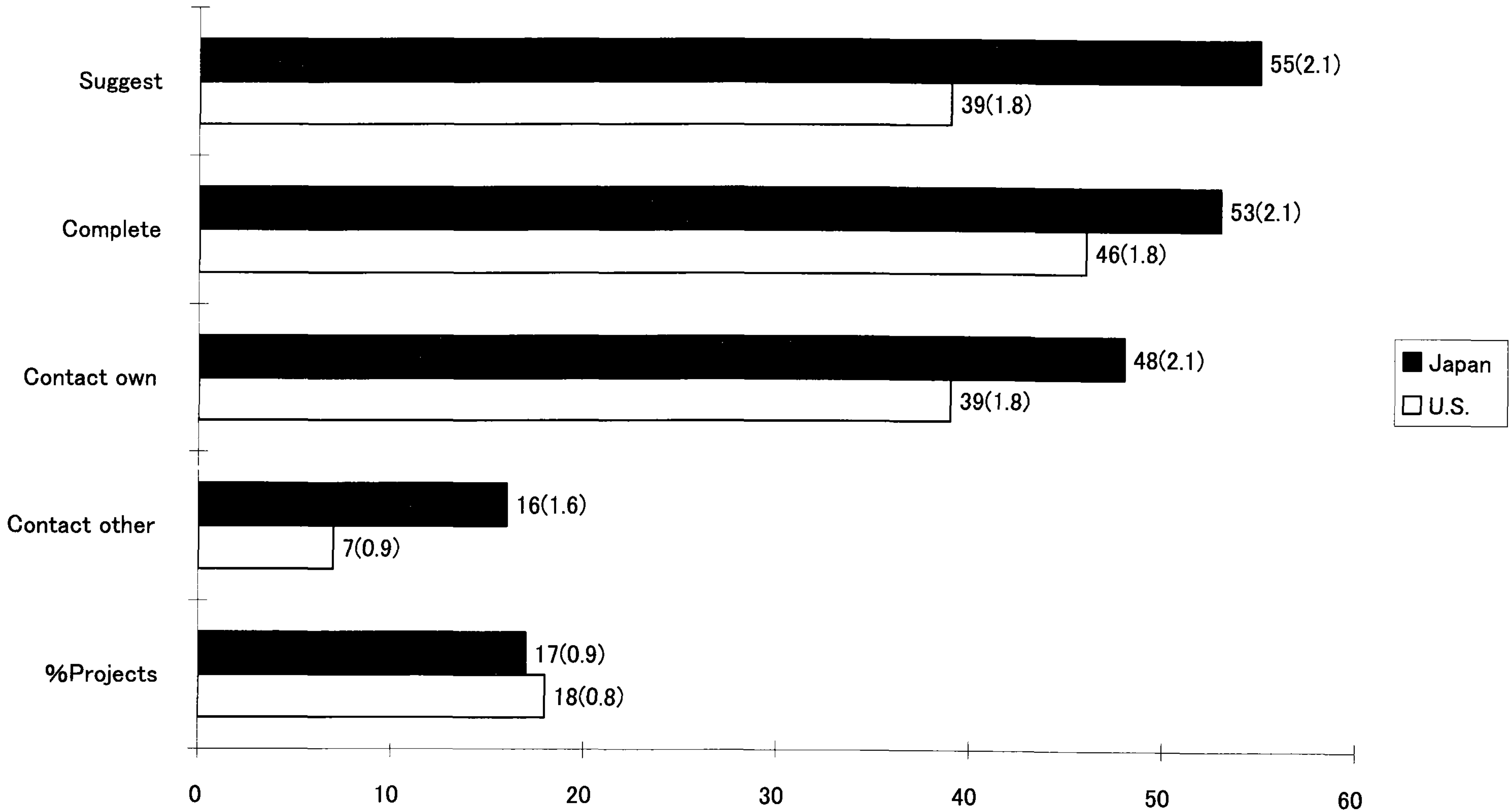

Figure 4. Importance to Industrial R&D of Information Sources on Public Research, U.S. and Japan

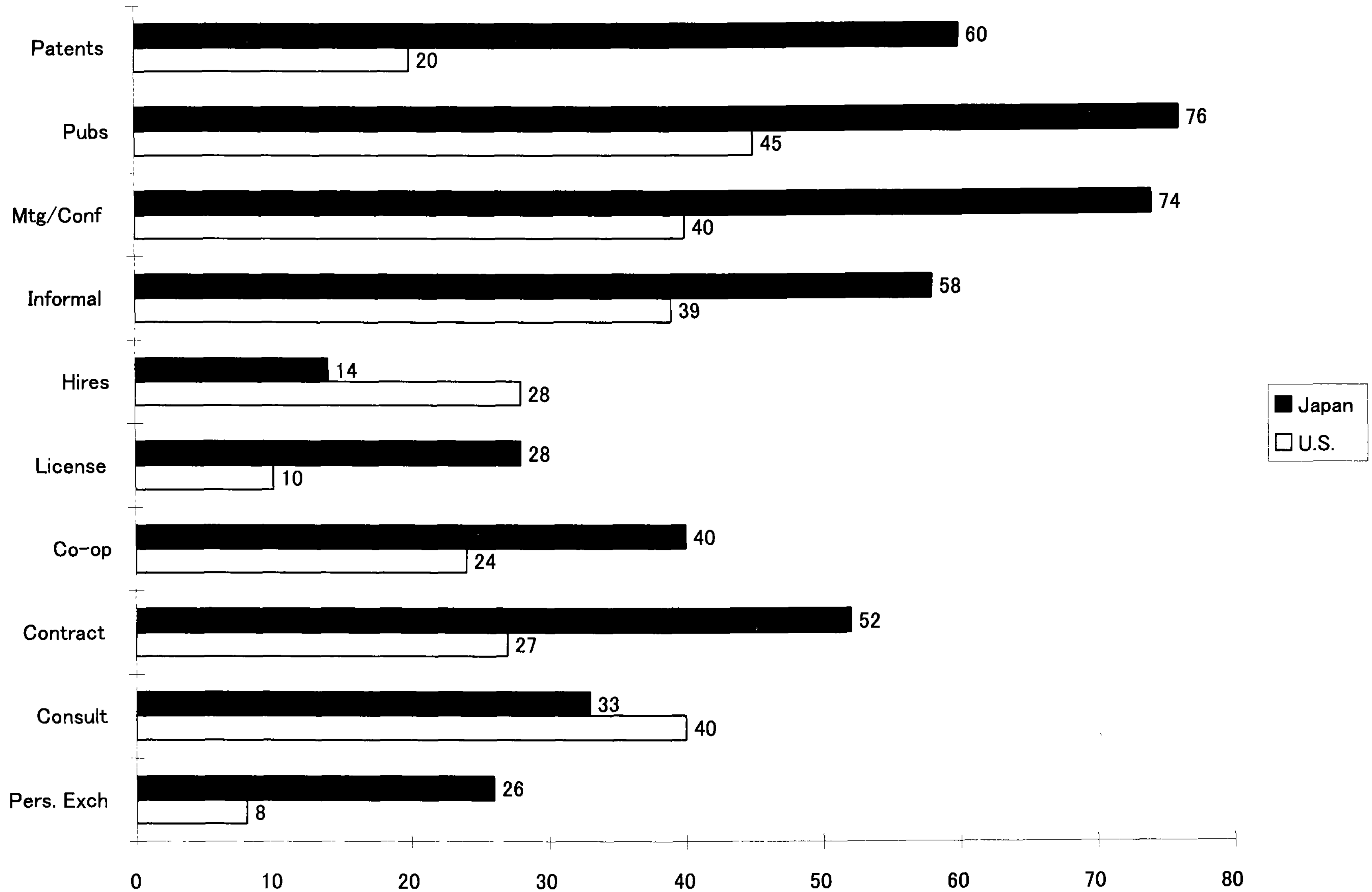

Figure 5. Sources of information, suggest new projects, US and Japan

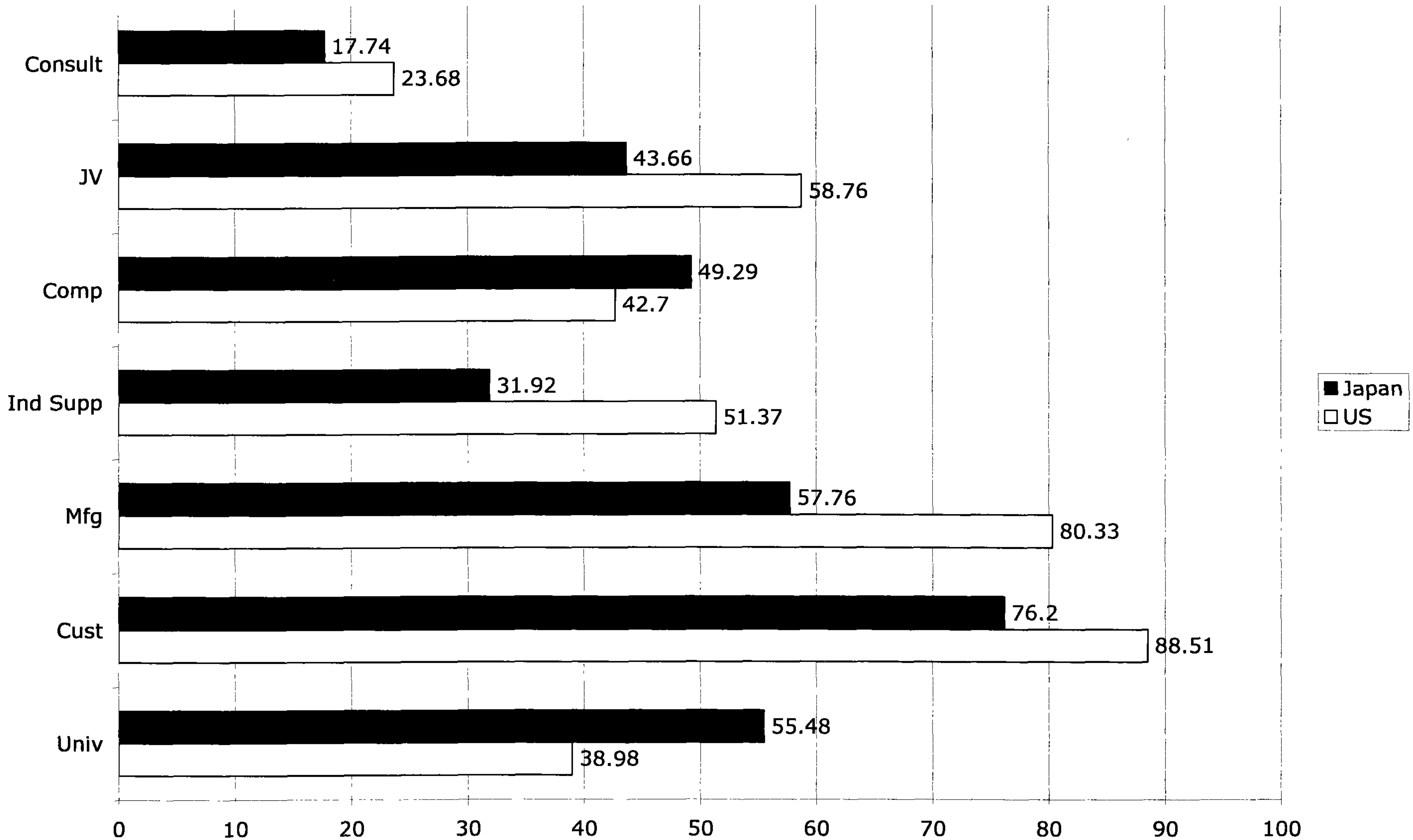

Figure 6. Sources of information, contribute to complete, US and Japan

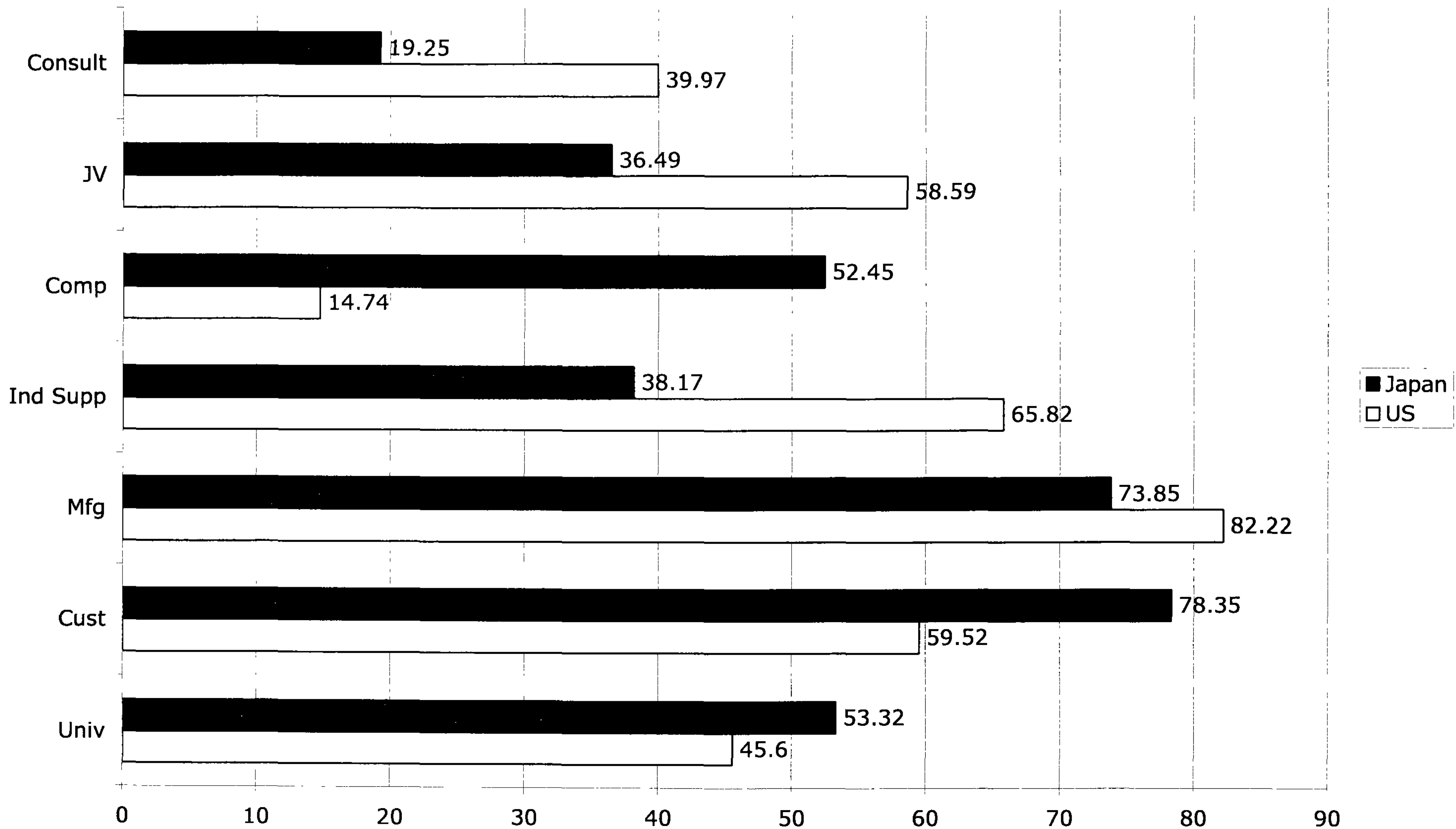

Table 5. Firm characteristics and information gathering strategies, U.S. and Japan.

Strategy	US		Japan		
	Mean	s.e.	Mean	s.e.	Sig.
Basic research%	5.2	.32	8.5	.43	***
Specialize%	43.6	1.28	26	1.21	***
Job rotation%	59.8	.02	75	.02	***
Local university R&D (index)	0.385	.011	.142	.006	***
Monitoring and information gathering%	11.7	0.37	12.2	0.34	ns
University publications as info. source (4-pt)	2.41	.04	3.00	.03	***
Informal interaction with university (4-pt)	2.25	.04	2.66	.04	***
Contract research with university (4-pt)	1.95	.03	2.46	.04	***
Temporary personnel exchange with univ. (4-pt)	1.95	.03	2.46	.04	***

Table 6a. Use of university research to suggest new projects and firm characteristics and information gathering strategies.

Suggest

	Estimate	StdErr	P>ChiSq	Estimate	StdErr	P>ChiSq	Estimate	StdErr	P>ChiSq	Estimate	StdErr	P>ChiSq	Estimate	StdErr	P>ChiSq
JAPAN	0.7866	0.1394	<.0001	0.7249	0.1422	<.0001	0.9522	0.176	<.0001	0.9346	0.1806	<.0001	0.427	0.2053	0.0375
LOG FIRM SALES	0.045	0.0507	0.375	0.0332	0.0514	0.5177	0.0565	0.055	0.3042	0.0537	0.0568	0.345	0.0239	0.0597	0.6884
LOG RD EES	0.2896	0.0491	<.0001	0.2959	0.0499	<.0001	0.2521	0.0551	<.0001	0.2846	0.0574	<.0001	0.2343	0.0602	<.0001
%BASIC				0.0251	0.0073	0.0006	0.0228	0.0077	0.0031	0.021	0.0078	0.0069	0.0157	0.0082	0.0555
SPECIALIZE							0.0033	0.0023	0.1464	0.0028	0.0023	0.2337	0.0015	0.0024	0.5296
ROTATION							0.303	0.1532	0.048	0.2946	0.1568	0.0603	0.1984	0.1657	0.2312
LOCALUNR&D							0.8691	0.2946	0.0032	0.8814	0.3031	0.0036	0.6946	0.3125	0.0262
MONITOR										0.0167	0.0077	0.0295	0.012	0.008	0.1343
READPUBS													0.1934	0.1001	0.0534
INFORMAL													0.1665	0.0923	0.0711
CONTRACT													0.5054	0.0916	<.0001
EXCHANGE													-0.014	0.1124	0.899
Intercept	-3.385	1.017		-3.204	1.0297		-3.998	1.1069		-4.36	1.1482		-5.059	1.2131	
N	1226			1205			1086			1043			1022		
chi-sq	176.58			187.83			187.75			192.49			254.95		
df	36			37			40			41			45		

Note: All models include industry controls (not shown).

Table 6b. Use of university research to contribute to project completion and firm characteristics and information gathering strategies.

Complete	Estimate	StdErr	P>ChiSq	Estimate	StdErr	P>ChiSq	Estimate	StdErr	P>ChiSq	Estimate	StdErr	P>ChiSq	Estimate	StdErr	P>ChiSq
JAPAN	0.597	0.1377	<.0001	0.5472	0.1412	0.0001	0.7381	0.173	<.0001	0.7384	0.1779	<.0001	-0.019	0.2104	0.9294
LOG FIRM SALES	0.1262	0.0487	0.0096	0.1255	0.0495	0.0113	0.1296	0.0527	0.0139	0.1339	0.0544	0.0139	0.1032	0.0592	0.0815
LOG RD EES	0.2023	0.0469	<.0001	0.2259	0.048	<.0001	0.1973	0.0531	0.0002	0.2141	0.0554	0.0001	0.1417	0.0609	0.02
%BASIC				0.0106	0.0072	0.1414	0.0087	0.0076	0.255	0.0091	0.0078	0.243	0.0003	0.0085	0.97
SPECIALIZE							0.0061	0.0022	0.0052	0.0055	0.0023	0.0149	0.0043	0.0024	0.0781
ROTATION							0.2687	0.1493	0.072	0.2457	0.1532	0.1089	0.1201	0.1678	0.4744
LOCALUNR&D							0.5543	0.2876	0.054	0.5106	0.2975	0.0861	0.232	0.319	0.467
MONITOR										0.0008	0.0077	0.9213	-0.008	0.0087	0.3783
READPUBS													0.2931	0.1017	0.004
INFORMAL													0.1817	0.0938	0.0526
CONTRACT													0.7154	0.0963	<.0001
EXCHANGE													0.1021	0.1153	0.3758
Intercept	-4.245	0.9834		-4.395	1		-4.798	1.0669		-5.066	1.1076		-6.375	1.2198	
N	1215			1193			1076			1035			1014		
chi-sq	152 45			163.45			160.13			170.66			297.35		
df	36			37			40			41			45		

Note: All models include industry controls (not shown).

Table 6c. Percent of research projects using university research and firm characteristics and information gathering strategies.

Percent Projects	Estimate	StdErr	P>ChiSq	Estimate	StdErr	P>ChiSq	Estimate	StdErr	P>ChiSq	Estimate	StdErr	P>ChiSq	Estimate	StdErr	P>ChiSq
JAPAN	0.4251	0.1171	0 0003	0.3128	0.1204	0.0094	0.5099	0.145	0.0004	0.5417	0.1481	0.0003	-0.424	0.1746	0.0151
LOG FIRM SALES	0.1614	0.0356	<.0001	0.1579	0.0363	<.0001	0.1318	0.0389	0.0007	0.1524	0.04	0.0001	0.0886	0.0427	0.0382
%BASIC				0.0215	0.0056	0.0001	0.0171	0.0059	0.0039	0.0133	0.006	0.0275	0.0078	0.0063	0.2157
SPECIALIZE							0.0042	0.0019	0.023	0.0028	0.0019	0.1457	-9E-05	0.0021	0.9657
ROTATION							0.3689	0.1265	0.0035	0.3482	0.1294	0.0071	0.1777	0.1375	0.1964
LOCALUNR&D							0.9091	0.2396	0.0001	1.0132	0.2447	<.0001	0 7269	0.2558	0.0045
MONITOR										0.0275	0.006	<.0001	0.0219	0.0062	0.0005
READPUBS													0.529	0.0867	<.0001
INFORMAL													0.2594	0.0779	0.0009
CONTRACT													0.414	0.0773	<.0001
EXCHANGE													0.2294	0.0932	0.0139
Intercept	-8.665	0.8403		-8.768	0.9218		-8.814	0.9525		-9.732	0.9487		-11.3	1.0201	
Intercept2	-6.819	0.7966		-6.908	0.8791		-6.949	0.9108		-7.73	0.8951		-9.221	0.9665	
Intercept3	-5.739	0.7892		-5.828	0.8716		-5.861	0.9034		-6.587	0.886		-8.013	0.9554	
Intercept4	-3.906	0.7801		-3.912	0.8618		-3.953	0.8935		-4.68	0.874		-5.874	0.9396	
N	1365			1321			1191			1143			1112		
chi-sq	117.29			129.45			143.91			159.67			334.01		
df	35			36			39			40			44		

Note: All models include industry controls (not shown).