R&D SPILLOVERS, APPROPRIABILITY AND R&D INTENSITY: A SURVEY BASED APPROACH

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ABSTRACT

We develop an empirical model of R&D spending that distinguishes between the degree to which firms expect to protect the profitability of their own inventions (what economists broadly call appropriability) and the R&D-related information flows across rivals that may affect that profitability. We test this model with data from the Carnegie Mellon Survey on Industrial R&D for the U.S. manufacturing sector that permit us to control for the effect of intraindustry R&D information flows on appropriability, and then separately observe the possibly countervailing effect of these flows on R&D itself. Key results include: 1.) the more appropriable are the rents to R&D, the higher the R&D intensity of an industry; 2.) greater effectiveness of selected appropriability mechanisms, particularly secrecy, dampens intraindustry R&D-related information flows; 3.) intraindustry R&D-related information flows lead to greater R&D intensity.

1. INTRODUCTION

R&D spillovers and the related notion of the appropriability of rents due to R&D have occupied central roles in academic analysis of the determination of innovative activity and performance. They also are the key concepts motivating policy interventions in support of industrial R&D. Despite their centrality in both research and policy, the effect of R&D spillovers and appropriability on R&D has not been clearly established. While there is now strong evidence supporting the argument that R&D spillovers have important effects on innovative performance and productivity growth (Griliches [1992]), empirical analyses of the direct effects of appropriability on the conduct of R&D have not yielded a consensus.

In this paper, we develop an empirical model of R&D spending that expressly distinguishes between the degree to which firms expect to protect the profitability of their own inventions (what economists broadly call appropriability) and the R&D-related information flows across rivals that may affect that profitability. It is important to do so because R&D-related information flows likely have two offsetting effects on R&D. First, to the degree that they diminish appropriability, they should dampen incentives to conduct R&D. They may also, however, increase the R&D productivity of the recipients of those flows, and, in turn, R&D at the industry level. Since these two effects of R&D-related information flows may therefore be offsetting, it will be difficult to observe a positive effect on R&D of both greater appropriability and R&D knowledge flows without also controlling for the negative relationship between those two variables.

To improve our understanding of the effects of appropriability and R&D-related information flows on R&D, we build a simultaneous equation system model that expressly reflects the links across these three variables at the industry level. We then test this model with data from the Carnegie Mellon Survey on Industrial R&D. The chief advantage of these data is that they provide separate measures of appropriability and intraindustry R&D information flows, permitting us to control for the effect of intraindustry R&D information flows on appropriability, and then more clearly observe the possibly countervailing effect of these flows on R&D itself.

To prefigure our key results, we find that the more appropriable are the rents to R&D, the higher the R&D intensity of an industry. We also find a negative relationship between the effectiveness of selected appropriability mechanisms (particularly secrecy) and intraindustry R&D-related information flows. Finally, and most importantly, we find that intraindustry R&D-related information flows lead to greater R&D intensity. This last result indicates that, controlling for the effect of intraindustry information flows on appropriability, intraindustry R&D information flows complement firms' own R&D efforts, underscoring the social welfare benefits of such flows.

Section 2 of the paper describes our conception of the ties that exist across R&D, appropriability and R&D-related information flows. In Section 3, we describe the data. Section 4 presents the detailed specifications and the construction of variable measures. In Section 5, we discuss estimation issues. In Section 6, we present the empirical results. Section 7 concludes the paper.

2. CONCEPTUAL APPROACH

In this paper, we present an empirical model relating R&D information flows, appropriability and R&D intensity to one another. Anticipating the available measures, appropriability is here characterized as the degree to which different appropriability mechanisms, such as secrecy, patents, or the exploitation of first mover advantages, increase the rents due to R&D. Without yet going into the details of the model, the simple schematic representation presented in Diagram 1 characterizes the central relationships that we posit.[1] This simple framework suggests, per standard theory, that the more effective are appropriability mechanisms such as secrecy or patents in protecting the profits due to invention, the greater are the incentives to conduct R&D. There is a reciprocal relationship between the effectiveness of the different appropriability mechanisms and the extent of intraindustry information flows. To the degree that R&D related information flows are stronger within an industry, the more difficult appropriation of rents to R&D will be, notwithstanding the particular appropriability mechanism employed. However, use of different appropriability mechanisms may, at the same time, diminish the extent and value to rivals of intraindustry information flows. For example, to the degree that secrecy is used and is effective, we would expect information flows to be less than if patents are used since patents, while offering protection, also disclose

[1] Diagram 1 omits the exogenous variables hypothesized to affect each of the dependent variables. These will be discussed below when we describe the detailed empirical specifications of the model.

information.

[DIAGRAM 1 ABOUT HERE]

In addition to affecting R&D intensity through their effect on appropriability, intraindustry R&D information flows may also directly condition R&D incentives by complementing firm R&D (Levin and Reiss [1984], Levin [1988] and Cohen and Levinthal [1989]) or by substituting for it (Spence [1984]). If the dominant effect of intraindustry R&D information flows on R&D effort is one of complementarity and no control for these flows is included, the effect of appropriability on R&D may appear to have an ambiguous effect assuming the relationship between such flows and appropriability is itself negative. We therefore expect that, once the negative effect of intraindustry information flows on appropriability itself is controlled, we are then in a position to see whether the direct effect of those flows on R&D is negative or positive, reflecting whether those flows, on balance, complement or substitute for own R&D.

Finally, we conjecture that innovative effort itself increases R&D information flows across rivals for two mutually reinforcing reasons. To the extent that more R&D is conducted, those flows should be greater, and to the degree that firms in an industry conduct more R&D, the more they are able to exploit those flows (Cohen and Levinthal [1989]).

3. DATA

The empirical analysis relies principally upon survey data from the 1994 Carnegie Mellon Survey (CMS) of industrial R&D in the United States. These survey data provide measures of the extent of knowledge flows both across competitors and from outside the industry, measures of the effectiveness of appropriability mechanisms, and measures of the R&D activity and performance of firms and industries, among other variables for a comprehensive sample of R&D performing firms, spanning industries such as food processing, polymer plastics, pharmaceuticals, semiconductors, computers, steel, medical instruments, and automobiles.

Building on prior empirical research showing that there are important cross-industry differences in the factors affecting technical advance (e.g. Nelson et al. [1967]; Cohen [1995]), data were collected at the business unit level rather than at the level of the enterprise as a whole.[2] The data come from a mail survey administered in the spring and summer of 1994. The respondents were R&D unit directors for manufacturing firms. The sample was randomly drawn from the eligible labs listed in *the Directory of American Research and Technology (DART)*[3] or belonging to firms listed in Standard and Poor's

[2] A business unit is defined to encompass a firm's activities within a given product market.

[3] This is the successor publication to Bowker *Publishing's Industrial Research Labs of*

COMPUSTAT, stratified by 3-digit SIC industry.[4] The survey yielded 1489 completed questionnaires, representing an unadjusted response rate of 46% and an adjusted response rate of 54%.[5] On the basis of descriptions of the business unit's markets, each respondent was assigned to a four-digit SIC code level industry. Given our greater confidence in our slightly more aggregate three-digit industry assignments, we will conduct our analyses using three-digit rather than four-digit level industry definitions.[6] Of the 77 three digit manufacturing industries represented in our sample we will focus on the 54 industries containing more than six observations in order to increase our confidence in the industry estimates.

We have also added to our survey data firm and industry-level data from other datasets. For example, we collected firm-level sales and employment data from COMPUSTAT and Dun and Bradstreet. We used the Census of Manufactures' 1992 Census of Manufactures' report MC92-S-2, "Concentration Ratios in Manufacturing," to obtain industry level data on sales.

Table 1 provides the descriptive statistics on firm and business unit size and R&D intensity for the sample. The average firm and business unit sales revenues are 4.4 billion and 1.7 billion dollars respectively. As the figures for the first and third quartiles indicate, the business unit and firm size distributions are quite broad, including numerous small firms. The sample mean R&D intensity, defined as business unit R&D divided by business unit sales, is 2.3%. A comparison between our industry-level R&D intensities and that of NSF for 1993 shows a reasonable correspondence with a correlation coefficient between the two series of .654. One reason that the correlation is not stronger is that our sample includes only R&D performing firms, while the NSF sample is drawn from the population of R&D performing and non-performing firms.

4. SPECIFICATIONS AND MEASURES

In this section, we will discuss our measures of R&D information flows, appropriability and R&D intensity and our empirical model for estimating the relations among these variables, based on Diagram 1. Our unit of analysis for this model is the industry, and thus all measures are constructed at the industry level. We begin by

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the United States, which served this purpose for the Levin et al. [1987] survey. Not confident in the accuracy or comprehensiveness of DART, we made over 5000 follow-up phone calls to develop our sample list.

[4] We also oversampled Fortune 500 firms.

[5] Our response rate was adjusted for respondent ineligibility inferred from our nonrespondent survey.

[6] One of our industries, semiconductors, is in fact a four-digit SIC (3674).

discussing the operationalization of our dependent variables, including our measures of appropriability, R&D information flows and R&D intensity, and then follow with a discussion of the construction of the exogenous variables appearing in the model. More detail on the construction of our measures appears in Appendix A.

4.1 The dependent variables: R&D intensity, appropriability and information flows

We construct our measure of **appropriability** from firms' responses to our survey questions concerning the effectiveness of each of six appropriability mechanisms, considered for process and product innovation separately. Specifically, our survey contained twelve items asking respondents about the percentage of innovations for which a given appropriability mechanism was effective for protecting the firm's competitive advantage from those innovations (i.e., the extent to which this mechanism is important). The key mechanisms considered in our survey include secrecy, patents, other legal mechanisms (e.g., copyright or design registration), complementary manufacturing facilities and know-how, complementary sales and service, and being first to market, asked separately for product and process innovations. Using an industry-level exploratory factor analysis of these twelve items, we find three distinct dimensions to appropriability, or what might be considered three distinct "appropriability strategies" emphasizing, respectively, capabilities and lead time, patents, and secrecy. We then use the factor loadings to construct for each respondent normalized factor scores for each of the three factors (for a more extensive discussion of factor analysis and our development of factor indices, see Appendix A). We then use simple averages for respondents in each industry to construct the following industry-level measures of appropriability:

CAPABILITIES/LEAD: For product and process innovations, the extent to which complementary manufacturing facilities and know-how, complementary sales and service and being first to market are effective in protecting innovations.

LEGAL: For product and process innovations, the extent to which patents and other legal mechanism are effective in protecting innovations.

SECRECY: For product and process innovations, the extent to which secrecy is effective in protecting innovations.

We will represent appropriability in our empirical model by these three dimensions. We choose not to combine these three dimension partly because we do not believe any combination is a priori defensible, and partly because we wish to examine the different effects that the effectiveness and use of these different strategies may have on R&D incentives, both directly and via their effects on R&D-related information flows across rivals.

In addition to our three measures of appropriability, we have the following measures for R&D-related information flows and R&D intensity:

INFO_RIVALS: Our measure of intraindustry R&D information flows is the percentage of respondents in an industry reporting that information from rivals suggested new R&D projects.

R&D_INTENSITY: We use a sales weighted average of the R&D intensities of the business units in each industry, where R&D intensity is business unit R&D divided by business unit sales.

4.2 System of equations

Reflecting the intuition represented in Diagram 1, we expect many of these five dependent variables to affect one another. Per our discussion in the prior section, industry R&D intensity should be influenced by the effectiveness of the appropriability strategies and the extent of the information flows across rivals. The effectiveness of the appropriability mechanisms will also affect the extent of information flows, and at the same time be affected by those flows. Moreover, R&D should affect the extent of information flows. To estimate relationships that involve pervasive mutual causation calls for a simultaneous equation system. Given five dependent variables, we will specify five equations. Before considering estimation of the system, we will describe for each of the five equations the right hand side variables and the construction of their measures.

While our R&D intensity equation discussed below can build on a strong foundation of theoretical and empirical work, there is little theory or empirical analysis of factors that might condition either the extent of R&D-related information flows or the effectiveness of different appropriability mechanisms. Thus, our empirical models explaining these factors are necessarily exploratory. These specifications are also opportunistic in the sense that they exploit the data elements that are available from our survey.

R&D Intensity Equation

Following prior work, we consider industry R&D intensity to be a function of three classes of industry-level variables, namely technological opportunity, demand, and the degree to which firms expect to appropriate returns to their innovations (cf. Cohen [1995]). In contrast to prior empirical studies on the determination of industry R&D intensity, we are able to distinguish explicitly between the effects on R&D of intraindustry information flows and appropriability.

To reflect appropriability, we include our factor-based indices for the effectiveness of the three key appropriability strategies as described above: LEGAL, CAPABILITIES/LEAD and SECRECY.

To the extent that intraindustry R&D-related information flows, INFO_RIVALS, influence R&D spending either by complementing firms' R&D efforts or by making those efforts more efficient, they are considered to reflect a dimension of technological opportunity (cf. Cohen [1995]) and are included on the right hand side. When thinking about the influence of R&D-related information flows on R&D intensity, one can divide those flows into two types: market-mediated flows operating through channels such as licenses, contracts and joint ventures, and nonmarket-mediated flows operating through channels such as publications, informal information exchanges across employees of rival companies, etc. While the former corresponds roughly to intraindustry pecuniary R&D spillovers (and hence do not necessarily diminish appropriation), the latter corresponds roughly to nonpecuniary intraindustry R&D spillovers and has been an object of enormous concern in the theoretical and empirical literature on R&D (Griliches [1992]). To the degree that there are nonpecuniary R&D spillovers, one can expect that firms will invest less than they should from a social welfare perspective. Why? Theory tells us that in the process of increasing the R&D productivity of rivals or making that R&D more efficient—and thus rendering a social benefit—nonpecuniary R&D spillovers diminish appropriability—the share of social benefits, and particularly the producers' surplus—going to the firm which is conducting the R&D. This in turn implies that firms will conduct less R&D than is desirable from a social welfare perspective. The empirical issue is that, largely due to the absence of separate measures for both appropriability and the R&D-related information flows associated with R&D spillovers, the conjectured direct effects of R&D spillovers on R&D incentives has not been clearly established.

Our measure of R&D related information flows reflects, however, the effects of all information flows across rivals, whether they be pecuniary (i.e., market-mediated flows such as licenses) or non-pecuniary (i.e., non-market mediated). To try to discern the effect of non-market mediated flows and thus intraindustry R&D nonpecuniary spillovers, we include a control on the right hand side of the R&D intensity equation for market-mediated R&D information flows (see Appendix A for details). The inclusion of this variable, denoted as MKT_CHANNELS, should allow us to interpret the effect of intraindustry R&D information flows (INFO_RIVALS) on R&D intensity as largely reflecting that of nonpecuniary intraindustry R&D spillovers.

Building on prior empirical work, our right-hand-side variables will also represent other dimensions of technological opportunity. Following Levin, Cohen and Mowery [1985] and Cohen, Levin and Mowery [1987], we include a survey-based measure of the vitality of the underlying scientific and engineering knowledge base, MAXSCI. Knowledge flows from supplying firms have also been considered in past work (e.g., Levin et al. [1985]) to be a dimension of technological opportunity since they can make firms' R&D more efficient. To represent the contribution to firms' R&D of information from suppliers, we include the variable, INFO_SUPPLIERS.

To control for the effect of industry demand, we include a variable, SALES_GROWTH, constructed from Census of Manufactures data and reflects each industry's average annual real rate of growth in output between 1987 and 1992. While we would have also liked to include industry price and income elasticities, they are not available.

Thus, our R&D equation predicts industry R&D intensity to be a function of the effectiveness of the three key appropriability strategies (LEGAL, CAPABILITIES/LEAD, SECRECY) and intraindustry R&D information flows (INFO_RIVALS), controlling for market mediated information flows (MKT_CHANNELS), information from suppliers (INFO_SUPPLIERS), the generic science base (MAXSCI), as well as demand growth (SALES_GROWTH).

Intraindustry R&D Information Flow Equation

In this equation, we hypothesize intraindustry information flows, INFO_RIVALS, to be a function of all of the other endogenous variables in the model, namely industry R&D intensity, R&D_INTENSITY, and the measures of the effectiveness of the three main appropriability strategies, represented by LEGAL, CAPABILITIES/LEAD and SECRECY. As described above, the rationales are that, as rivals conduct more R&D, more information should be produced that can flow into the firm. Reinforcing that positive relationship, to the degree that firms in an industry conduct more R&D, the more able they are to exploit those flows (Cohen and Levinthal [1989]). We expect that different appropriability mechanisms may have different effects on the extent of intraindustry information flows. For example, to the degree that secrecy is used and is effective, we would expect information flows to be less than if patents are used since patents, while offering protection, also disclose information.

Exogenous variables expected to affect the information flows from rivals going to any one firm include, first, the number of "technological rivals" within an industry—that is the number of other firms that are working in the same or related technological domains, denoted as TECH_RIVALS. We conjecture that as this number rises, the greater and more important are the flows. We also suspect that extraindustry knowledge flows may also affect intraindustry knowledge flows in a couple of ways. To the extent that ties between firms and extraindustry information sources, whether they be suppliers, buyers, or universities and government labs, are stronger, the greater the likelihood of information flowing indirectly through those sources to rivals. Ties to universities and public research more generally may have another affect. Strong ties with such sources may signal that there is a greater generic knowledge base within the industry, and firms may consequently be in a better position to evaluate and exploit the knowledge spillovers of rivals. Thus, we examine the influence on information spillovers of three sources of extraindustry knowledge, namely public research (encompassing the research of universities and government institutes), suppliers and buyers.

The measures for the extraindustry knowledge flows originating from universities and government labs and research institutes are of two types. First, our survey offers various measures of the importance of information from public research to each firm's R&D, INFO_UNIV. Second, we have a measure of the importance of non-market "public" channels (conferences or meetings, publications, and informal information exchange), which we call UNIV_PUB. To reflect the role of information originating from suppliers, we again use the variable, INFO_SUPPLIERS, whose construction is described above. To operationalize the notion of information flows from customers, we use the percent of respondents who report that information from customers suggested new projects, INFO_BUYERS.

Thus, we are modeling R&D information flows, INFO_RIVALS, as a function of R&D_INTENSITY and our three measures of appropriability (LEGAL, CAPABILITIES/LEAD, SECRECY), controlling for market mediated information flows (MKT_CHANNELS), the number of technological competitors (TECH_RIVALS), and extraindustry information from suppliers (INFO_SUPPLIERS), customers (INFO_BUYERS) and universities (INFO_UNIV and UNIV_PUB).

Appropriability Mechanism Equations

We specify three equations corresponding to the factor-based effectiveness scores derived for each of the three groups of appropriability mechanisms described above, including: 1.) lead time and complementary capabilities (CAPABILITIES/LEAD); 2.) secrecy (SECRECY); and 3.) patents and other legal mechanisms (LEGAL). In each of these three equations, to reflect the contribution to appropriability of each type of mechanism, we need to control for the effectiveness of the other strategies. Thus, we include on the right hand side the effectiveness scores for the other two groups of appropriability mechanisms.

We also include in each of these three equations our measure for intraindustry information flows, INFO_RIVALS, the control for pecuniary flows, MKT_CHANNELS, the measure for the number of technological rivals facing each firm, TECH_RIVALS, and a control for the mean percentage of R&D dedicated to product innovation in each industry, PROD_R&D. We include our measure of intraindustry information flows because, per the discussion of Diagram 1, the greater are such flows, the less appropriability should be in general. We include TECH_RIVALS to reflect the argument that the greater the number of technological rivals, the quicker the rents from innovation will be competed away. We have included PROD_R&D to reflect the notion that one group of appropriability mechanisms, such as LEGAL, may be more suited to product innovations, while another, such as SECRECY, may be more suited to process innovations (cf. Levin et al. [1987]).

CAPABILITIES/LEAD Equation

In the CAPABILITIES/LEAD equation, we have included the variable INFO_BUYERS and INFO_SUPPLIERS, both discussed above. We include these two variables in the CAPABILITIES/LEAD equation to reflect the possibility that these measures would reflect the strength of the relations between an industry's firms and their buyers and suppliers, and that the stronger these ties, the greater the ability of firms to capture a lead time advantage. We also conjecture that firms are more able to exploit complementary capabilities to the extent that cross-functional communication channels within the firm are stronger. Our variable COMM_PRODN measures the frequency of interaction between R&D and manufacturing.

So, in our CAPABILITIES/LEAD equation, we include our other two measures of appropriability (LEGAL and SECRECY) and R&D information flows (INFO_RIVALS), controlling for cross-functional communication (COMM_PRODN), and extraindustry information from suppliers (INFO_SUPPLIERS) and customers (INFO_BUYERS).

SECRECY Equation

In the equation for SECRECY, we include three explanatory variables in addition to those that are common across all three appropriability mechanism equations. First, we conjecture that as knowledge is more generic and more publicly accessible, secrecy will be less effective as an appropriability strategy. To roughly capture this effect, we include our variable that represents the important of information from universities (INFO_UNIV), as well as the importance of public, non-market channels such as publications and public meetings in conveying university research results, UNIV_PUB. We also believe that in some industries, the very nature of the technology can make secrecy less effective as a strategy. Specifically, innovations in some industries more than others lend themselves to reverse engineering. Our measure, REVERSE_ENGIN, estimates the importance of rivals' products as a source of information (via, for example, reverse engineering). Similarly, an important limitation on the effectiveness of secrecy is the movement of technical personnel from one firm to another. Our measure, LABOR_MOBILITY, estimates the importance of recent hires as a source of information about rival R&D.

Therefore, in our SECRECY equation, we include our other two measures of appropriability (LEGAL and CAPABILITIES/LEAD), and R&D information flows (INFO_RIVALS), controlling for the importance of reverse engineering (REVERSE_ENGIN), recent hires (LABOR_MOBILITY), and the generic quality of knowledge (INFO_UNIV and UNIV_PUB).

LEGAL Equation

In the equation for LEGAL we include four explanatory variables in addition to those that are common across all the appropriability mechanism equations. First, we include INFO_UNIV and UNIV_PUB to reflect the notion that in the domains where there is a well defined science base, and publication of scientific findings is the norm, the know-how tends to be more codifiable and, in turn, patentable.

Also, it is commonly recognized that the effectiveness of patents vary enormously across technology areas. Our measure, MED_SCIENCE, represents the importance of "medical and health science" in a given industry. This seemed to be the field that best represented the "patentability" of the underlying science.[7] To further reflect the notion noted above that the stronger is the underlying scientific knowledge base in general within an industry, the more patentable is the technology, we have also included MAXSCI, our measure of the importance of the most relevant academic field.

For our final equation, we predict LEGAL to be a function of our other two measures of appropriability (SECRECY and CAPABILITIES/LEAD) and R&D information flows (INFO_RIVALS), controlling for the generic quality of knowledge (INFO_UNIV and UNIV_PUB), the importance of medical and health science (MED_SCIENCE) and the overall importance of the most relevant academic field (MAXSCI).

Table 2 provides the variable names, measures and means and standard deviations for all the variables used in the model.

[INSERT TABLE 2 ABOUT HERE]

5. ESTIMATION

We have presented a model in which five variables, including intraindustry R&D information flows, industry R&D intensity, and the effectiveness of the three appropriability strategies are simultaneously determined. To estimate this system of five equations, we employ two stage least squares (2SLS).[8] Although more appropriate for a larger sample, three stage least squares (3SLS) are also employed, partly to exploit its efficiency properties and partly as a robustness check on the two stage least squares results. For each equation in the 2SLS and 3SLS results, we will apply the Basmann test for overidentifying restrictions. This test tends to reject the null hypothesis of no overidentifying restrictions in small samples like ours (N=54), however.

Since we are examining industry-level effects, all variables are expressed as industry averages. To control for sampling error in these estimates, and as a partial control for the heterogeneity of firms within our sample industries, we weight each case

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[7] The other fields considered included chemistry, biology, physics, computer science, materials science and mathematics. Biology performed comparably to our MED_SCIENCE variable, but was highly collinear with it and thus was not included.

[8] For the 2SLS and 3SLS estimations, we employ six predetermined variables in the first stage instrumental variables estimation that are not included in our structural model. These include a measure of the level of industry demand, a measure of the importance of non-market channels of information flow across rivals, three measures for the U.S., Japan and Europe of the frequency with which respondents receive useful information from rivals, and a subjective Likert score reflecting the relevance of the most relevant university research field of engineering.

by the square root of the number of observations in each industry.

We have run Hausman [1978] specification tests to test for the simultaneity that we assume to exist. In essence, the null hypothesis tested is that both estimators are consistent, but only the ordinary least squares (OLS) estimator is asymptotically efficient. We report the Hausman test statistics in each of the five tables below the 2SLS results. In no case are we able to reject the null hypothesis, suggesting that estimating the equations as a simultaneous system may not be necessary or appropriate. Yet, as pointed out by Johnston and DiNardo [1997] among others, the test results can be inconclusive, first, because it is designed for large samples, and, second, because it may either reflect that the endogeneity bias of the parameters estimated with OLS is not serious or that the predetermined variables excluded from the structural equations are only weakly correlated with the endogenous variables. Notwithstanding the appropriateness of the Hausman specification test for a small sample such as ours, we include the OLS results along with the 2SLS and 3SLS results.

6. RESULTS

Tables 3 through 7 present the ordinary least squares and the two and three stage least squares (2SLS and 3SLS) estimates for the five specifications. Our discussion will focus largely on the 2SLS and 3SLS estimates. We will lead our discussion with the two equations that are substantively the most important: the R&D intensity equation and the intradindustry R&D-related information flow equation.

R&D INTENSITY EQUATION

Presented in Table 3, the featured results in the industry R&D intensity equation are those for our intraindustry R&D information flow variable, INFO_RIVALS, and the variables representing the effectiveness of the three appropriability strategies, SECRECY, CAPABILITIES/LEAD and LEGAL. The coefficient estimate for INFO_RIVALS is positive and significant at the .01 confidence level in the 2SLS and the 3SLS results, suggesting that the direct influence of intraindustry R&D information flows is strongly complementary to R&D at the industry level. This positive effect of INFO_RIVALS is perhaps the strongest, most robust result of the entire analysis, holding up across alternative estimation methods and specifications. As suggested above, we included the variable, MKT_CHANNELS to control for the pecuniary intraindustry R&D spillovers associated with information flows. Given this control, our positive, significant coefficient estimate for INFO_RIVALS further suggests that nonpecuniary intraindustry R&D spillovers are associated (when controlling for appropriability as we do) with a net complementarity effect on R&D (per Levin and Reiss [1984], Levin [1988]) rather than an efficiency or substitution effect (per Spence [1984]). The coefficient estimate for MKT_CHANNELS is negative in both the 2SLS and 3SLS results, and significant in the 3SLS results, suggesting that information on competitors' R&D derived through market channels tends to substitute for own R&D.[9]

[INSERT TABLE 3 ABOUT HERE]

The three variables representing the effectiveness of the different appropriability strategies exercise positive effects on industry R&D intensity across the 2SLS and 3SLS estimation methods, but only the effect of LEGAL (i.e., patents) is significant across all estimation methods. In the 3SLS results, all are significant at conventional levels of confidence. Thus, we appear to have distinguished a direct positive effect on industry R&D intensity of both intraindustry information flows and appropriability. It must be noted, however, that with the exception of the result for LEGAL, the significance of the effect for other two appropriability strategies, SECRECY and CAPABILITIES/LEAD is not necessarily robust to alternative specifications.

We also find a negative and significant effect of information flows from suppliers, INFO_SUPPLIERS, suggesting that such information substitutes for own R&D, a finding that resembles that of Cohen, Levin and Mowery [1987]. Our control for the effect of demand, SALES_GROWTH, is positive as expected and significant in the 2SLS (and OLS) but not the 3SLS results. Our control variable representing the effect of the vitality of the underlying science base, MAXSCI, was positive, as expected, but never significant at conventional levels (only at the .10 confidence level in the OLS results).

Thus, we find that appropriability does increase R&D <u>and</u> that, controlling for appropriability, intraindustry R&D information flows also increase R&D.

INTRAINDUSTRY R&D INFORMATION FLOWS EQUATION

Presented in Table 4, the 2SLS and 3SLS results suggest that the particular appropriability mechanisms that tend to be used in industries affect information flows. The clearest and most robust effect is exercised by SECRECY, which has a negative and significant effect on R&D information flows across rivals across all three estimation methods. The coefficient estimate for CAPABILITIES/LEAD is also negative in both the 2SLS and 3SLS results, but is only significant in the 3SLS results. The coefficient estimate for LEGAL is positive but not significant in the 2SLS results, and negative but not significant in the 3SLS results. Of these results, the negative and significant effect of SECRECY is most robust. A negative effect of secrecy conforms to priors, suggesting that to the degree that within industries secrecy is used and effective, R&D information flows are dampened. We would not have necessarily predicted a negative effect on information flows of CAPABILITIES/LEAD. One can easily imagine, however, that in

[9] Reflecting this effect, when we drop MKT_CHANNELS from the specification, permitting INFO_RIVALS to reflect both pecuniary and nonpecuniary spillovers, the coefficient estimate on INFO_RIVALS drops by about a standard error.

industries where the exploitation of complementary capabilities and lead time is important, firms cannot wait for a rival to provide it with project ideas (which is the basis of our information flow measure), by which time the rival may already have an unassailable advantage. Another result of interest is that LEGAL apparently exercises little or no effect on intraindustry R&D information flows. This may be explained by the fact that while patents disclose information, they also provide protection for that information to some degree, and thus diminish the value of the information received.

[INSERT TABLE 4 ABOUT HERE]

As expected, higher industry R&D intensity (R&D_INTENSITY) appears to contribute significantly to intraindustry information flows. Also, the coefficient estimate for TECH_RIVALS is positive (though in the 3SLS not quite significant), offering some support for the claim that a greater number of technological rivals increases R&D information flows within an industry.[10] While INFO_UNIV, the variable representing the importance to an industry of university research, is never significant, the coefficient estimate for UNIV_PUB is positive and significant in both sets of results. Thus, to the degree that channels conveying research originating from university and government labs is more important to industrial R&D labs, the greater are the intraindustry R&D information flows across rivals. This could suggest, as conjectured, that a stronger published generic knowledge base may augment information flows across rivals. Alternatively, this result may simply signal that public channels of information flow across competitors are stronger when similar channels between universities and industry are stronger.

The importance of information flows from buyers (INFO_BUYERS) had no effect. The effect of information flows from suppliers (INFO_SUPPLIERS), however, had a positive effect across the 2SLS and 3SLS results, significant in the 3SLS results and marginally significant in the 2SLS results. This result provides some support to the argument that suppliers may serve as an indirect channel for information flows between rivals. Our variable controlling for the importance of market-mediated information channels like licensing is positive in both sets of results, though significant only in the 3SLS results.

Thus, we find that industry R&D increases extramural information flows and that secrecy decreases them.

APPROPRIABILITY STRATEGIES EQUATIONS

To consider our results in the three appropriability mechanism equations, we will first consider those key results which cut across all three specifications in Tables 5

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[10] We also ran a version of the model in which TECH_RIVALS was specified as a sixth dependent variable in our model. None of the featured qualitative results changed.

through 7. We will then consider the results for those variables which are specific to each equation.

Results across All Three Appropriability Strategies Equations

Per our qualitative model presented in Diagram 1, the key result we are looking for across all three of these equations is the effect of intraindustry R&D information flows upon appropriability. Although we expected to observe a negative effect across all three types of appropriability mechanisms, we barely see any effect at all. As discussed further below, recall that we do observe, however, a negative relationship between the effectiveness of appropriability strategies and INFO_RIVALS in the INFO_RIVALS equation. The only evidence of the conjectured negative effect of INFO_RIVALS on appropriability in these equations is in the equation for SECRECY. Here, we find that a correlate of INFO_RIVALS, the variable LABOR_MOBILITY, is negative and significant across all the results. When the variable is dropped from the specification, INFO_RIVALS becomes negative and significant in the 2SLS and 3SLS results.

Recall that we tried to allow INFO_RIVALS to reflect largely the effect of nonpecuniary intraindustry R&D spillovers by including a measure of the importance of market-mediated information flows, MKT_CHANNELS. The effect of MKT_CHANNELS is positive and significant in both the CAPABILITIES/LEAD and LEGAL equations. In the case of its role in the LEGAL equation, it may reflect a reverse causation; where legal mechanisms are strong, mechanisms like licensing or contracts are likely to be more important in general, and thus more important as information channels.[11] Its positive, significant coefficient in the CAPABILITIES/LEAD equation may suggest that, just like strong internal links across functions may be critical to exploiting complementary capabilities, strong external links may also be key, and many of those may be market-mediated. MKT_CHANNELS exercises no influence in the SECRECY equation.

Reflecting the influence on appropriability of the intensity of competition within a market, our measure of the number of close technological rivals in a market, TECH_RIVALS, exercises a negative and significant effect for the 2SLS and 3SLS results for the LEGAL equation and in the 3SLS results for the CAPABILITIES/LEAD equation (and is negative but not significant in the 2SLS results), suggesting that both of these appropriability strategies are weaker in the face of a greater number of technological rivals. TECH_RIVALS exercises no significant effect in the SECRECY equation.

The coefficient estimate for our other control variable reflecting the percent of

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[11] We control for this possible endogeneity by using an instrument for MKT_CHANNELS constructed by regressing it against all the right-hand-side variables and the other predetermined variables in the system. In this new specification, MKT_CHANNELS ceases to have a significant effect.

R&D dedicated to product innovation, PROD_R&D, is positive and significant in the LEGAL and CAPABILITIES/LEAD equations, and is negative in the SECRECY equation, though significant only in the 3SLS results.

Thus, we find only weak effects of information flows on appropriability, controlling for the effects of appropriability on information flows.

Results for Variables Appearing in Only the SECRECY Equation

[INSERT TABLE 5 ABOUT HERE]

The results for the SECRECY equation are presented in Table 5. With regard to the influence of the effectiveness of the other appropriability strategies on SECRECY, we find that both LEGAL and CAPABILITES/LEAD have positive effects, though significant (at the .10 confidence level) only in the 3SLS results. We interpret these results as suggesting that, under some circumstances, secrecy may complement the other two appropriability strategies. For example, firms may try to keep findings secret that they intend to patent, at least until the application is filed and probably even until it is issued, and will also keep major innovations secret as long as possible to achieve as much of a lead time advantage as possible.

Across both the 2SLS and the 3SLS results for the SECRECY equation we observe that, as public channels (e.g., publications, conferences) conveying public research (i.e., that of universities and government) to industrial R&D labs (i.e., UNIV_PUB) become more important, SECRECY increases. While it is hard to believe that secrecy becomes more effective as a means of appropriation under such circumstances, it is easy to believe that as the amount of relevant technical information conveyed through public channels increases, firms may become more concerned about and attentive to keeping their own findings secret, even while it may be more difficult to do so. Consistent with this interpretation, the effect of INFO_UNIV, reflecting the importance of public research to industrial R&D, is negative and significant in both the 2SLS and 3SLS results, perhaps suggesting that for industries where the generic or publicly accessible knowledge base is stronger, secrecy is indeed less effective.

As noted above, the effect of LABOR_MOBILITY is, as conjectured, negative and significant across the 2SLS and 3SLS results. The coefficient for REVERSE_ENGIN, reflecting the importance of rival products as a source of information (via reverse engineering, for example), is not significant, though negative as predicted.

Results for Variables Appearing in Only the CAPABILITIES/LEAD Equation

[INSERT TABLE 6 ABOUT HERE]

The results for the CAPABILITIES/LEAD equation are presented in Table 6. With regard to the influence of the effectiveness of the other two appropriability strategies, namely SECRECY and LEGAL, on the effectiveness of the CAPABILITIES/LEAD strategy, we observe no significant effect of SECRECY, but a negative effect of LEGAL (significant in the 3SLS results), perhaps suggesting that the exploitation of complementary capabilities and lead time is to some degree exclusive of a strategy based, for example, on patents.

In the motivation for our specification provided above, we suggested that strong internal links across functions and strong upstream and downstream ties may be strengthen an appropriability strategy based on lead time and complementary capabilities. We find some support, though limited, for this argument. The coefficient estimates for information flows from customers (INFO_BUYERS) and those from suppliers (INFO_SUPPLIERS) are positive in both sets of results, although signficant (at the .10 confidence level) only in the 2SLS results. Internal information flows, specifically those between the R&D labs and production (COMM_PRODN), have a stronger effect, with a positive and significant coefficient estimates in both the 2SLS and 3SLS results. All these results may, however, reflect some degree of endogeneity. For example, once a firm decides to embark on a strategy involving the exploitation of complementary capabilities and lead time advantages, the firm may at that point decide to strengthen the communication links that may be required to successfully implement such a strategy.

Results for Variables Appearing in Only the LEGAL Equation

[INSERT TABLE 7 ABOUT HERE]

The results for the LEGAL equation are presented in Table 7. In the regression with LEGAL as the dependent variable, we again find a relationship with CAPABILITIES/LEAD that is symmetric to that found when LEGAL is the independent variable in the CAPABILITIES/LEAD equation; the coefficient estimate for CAPABILITIES/LEAD is negative and significant, suggesting the two strategies tend to be exclusive of one another. SECRECY has no significant effect in this equation.

We do not find strong support for the propositions that patents are particularly more effective where the underlying science base (i.e., MAXSCI) is stronger, or in industries where medical and health science (MED_SCIENCE) is strong, although the coefficient estimates on both variables are positive in both sets of results. We also find no effect for the importance of information from universities (INFO_UNIV). A Wald test for the joint significance of these three variables, $\chi^2(3) = 2.14$, is not quite significant at the .10 confidence level. We do find, however, that LEGAL is lower in those industries where university research flows to industry via public channels such as publications and public meetings and conferences (i.e., where UNIV_PUB is higher), possibly suggesting in those domains where more relevant knowledge is placed in the public domain (via publication), it is more difficult to patent or patents are more likely to be invalid when put to a court test.

FIVE EQUATION SYSTEM: THE OVERALL RESULTS

In this section, we will review the key results that speak to our qualitative model represented in Diagram 1. In addition to reviewing these results, we will also consider a number of methodological issues.

As conjectured, we observe a strong effect of R&D information flows on industry R&D intensity when we control for the effectiveness of the three appropriability strategies considered. Moreover, given our control for pecuniary R&D spillovers, it is sensible to interpret this effect as reflecting that of intraindustry non-pecuniary R&D spillovers. What was not obvious a priori was the sign of this effect. As conjectured by Levin [1988], we observe strong complementarity between industry R&D intensity and these intraindustry R&D information flows. This result is robust and clear. The second result of interest is that of appropriability. Although this result is more fragile than that for intraindustry R&D information flows, we observe the expected positive effect across the three appropriability strategies, and these are particularly significant in the 3SLS results.

As conjectured, we also observe a significant effect on intraindustry R&D information flows of two of the three appropriability strategies. Except with regard to the influence of SECRECY, it was not clear a priori what the direction of this effect would be. Indeed, we found a clear and robust negative effect of SECRECY, as well as a negative effect—though significant only in the 3SLS estimates—of CAPABILITIES/LEAD. Befitting the policy role of patents as a vehicle for information disclosure as well as appropriation, it was not surprising that the effect of LEGAL was insignificantly different from zero, presumably reflecting the explicitly offsetting effects of patents.

The one area where our results are quite weak are the conjectured negative effects of intraindustry R&D information flows, and particularly those flows representing nonpecuniary R&D spillovers, on appropriability itself (reflected in our measures of the effectiveness of the three appropriability strategies). Only the effect on SECRECY supports this hypothesis, and that is only when a correlate of INFO_RIVALS is dropped from the specification. The importance of this conjectured negative relationship was our argument that, only when it is controlled in a simultaneous system, can one clearly observe a positive effect of appropriability on R&D spending itself. Our results still, however, suggest this argument has merit, but not quite in the way we anticipated. Specifically, we do indeed observe a negative relationship between appropriability and intraindustry R&D spillovers, but not in the equations that consider the determination of appropriability. As noted above, that relationship is predominantly observed in the intraindustry R&D information flows equation in the form of a negative effect of SECRECY and CAPABILITIES/LEAD.

Another question is whether we benefit from specifying these equations as a simultaneous system. We have several test statistics that speak to the issue. First, at an operational level, to identify the system, we have restricted coefficient values to equal zero for some exogenous and other predetermined variables. To consider whether these restrictions may be invalid, we computed the Basmann [1960] test statistic for overidentifying restrictions for each of the equations for both the 2SLS and 3SLS estimations. These test statistics are presented in Tables 3 through 7. We cannot reject the null hypothesis that the imposed restrictions are valid for four of the five equations. For only the SECRECY equation can we reject the null hypothesis at the .05 level confidence level for the 2SLS estimation, and at the .10 confidence level for the 3SLS estimation. This is heartening since the Basmann statistic tends to reject the null hypothesis too frequently for small samples such as our own which only has 54 industry observations.

In our discussion above of estimation issues, we noted that the Hausman specification test rejects our assumption of endogeneity for each of our equations (as it does for the system as a whole). At the same time, we offered numerous reasons to be skeptical of these test results, particularly the fact that it is not reliable for small samples. We suggest that a comparison across the OLS, 2SLS and 3SLS results, particularly in the R&D intensity equation, suggests that simple OLS would indeed lead to simultaneity bias for key parameter estimates. It is true that already in the simple OLS estimation of the R&D intensity equation, we observe a positive effect of the featured variables, namely intraindustry R&D information flows and the measures of the effectiveness of the various appropriability mechanisms, though the statistical significance of the latter is low. Once we do control for simultaneity, however, the coefficient estimates for all these variables increase by approximately two standard errors (and more when we go to the 3SLS results), with increases in statistical significance. We find a similar pattern in the coefficient estimates as we move from OLS to 2SLS and 3SLS for almost all the featured endogenous variables in the intraindustry R&D information flows equation, namely industry R&D intensity and SECRECY and CAPABILITIES/LEAD.

With regard to goodness of fit, we observe the R-squared's to be .48 or above for OLS results for each equation. The system-weighted R-squared for the 3SLS estimation is .58. These various goodness of fit measures suggest that our model fits the data reasonably well.

7. CONCLUSION

Most of our results based on our industry-level simultaneous equation system model of R&D intensity, appropriability and intraindustry R&D information flows (cum intraindustry R&D spillovers) support our conjectures regarding the relationships across these variables. The effectiveness of all three of the key appropriability strategies are positively related to R&D intensity, as are R&D information flows from rivals. Moreover, intraindustry R&D information flows are negatively related to the effectiveness of the dominant means by which firms appropriate returns to their inventions, namely the use of secrecy and the exploitation of first mover advantages and complementary capabilities.

From a policy perspective, several of the relationships are worthy of note. First, intraindustry R&D spillovers appear to have a robust, positive effect on the R&D intensity of rivals. Such complementarity effects of intraindustry R&D spillovers affirm the wisdom of government (i.e., ATP) encouragement of projects that lend themselves to such spillovers. Second, our results suggest that as appropriability declines R&D intensity tends to decline, confirming the conventional wisdom that the likelihood of market failure to be greatest in those industries where appropriability is weak, ceteris paribus. Finally, of all the appropriability strategies, that based on secrecy robustly diminishes intraindustry R&D spillovers and has the weakest positive incentive effect on R&D intensity, suggesting that, of all the ways that firms can protect their profits due to invention, secrecy imposes the greatest social welfare. In contrast, patents have no discernible effect on intraindustry R&D spillovers and appear to diminish intraindustry R&D spillovers the least of all the mechanisms. These observations suggest that to the degree that policymakers consider R&D projects for subsidy, it is worth inquiring about the particular appropriability strategies a firm intends to employ to protect their invention, and, to the extent that the use of secrecy can be restrained, it should be.

Our analysis is subject to numerous qualifications. Our survey-based measures are undoubtedly subject to considerable measurement error. Some of our specifications are somewhat ad hoc when there is little theory to offer guidance, and are at times opportunistic with regard to the availability of measures. Although our 54 industries provide relatively broad and detailed coverage of the U.S. manufacturing sector, we are also estimating a complex set of relationships with relatively few industry-level observations. Finally, although the central results are robust, some results are not robust across alternative specifications and estimation methods. Nonetheless, our results are sufficiently sensible to suggest that survey-based measures may be useful for examining the relationships across R&D intensity, spillovers and appropriability and future attempts to collect original data on the factors conditioning innovation should prove to be worthwhile.

APPENDIX A: MEASURE CONSTRUCTION

A1. FACTOR-BASED INDICES

ENDOGENOUS VARIABLES

The endogenous variables in our model include three factor-based indices for appropriability: CAPABILITES/LEAD, LEGAL, and SECRECY. We begin by briefly introducing factor analysis and then describe our procedure for creating the factor-based indices of appropriability.

Appropriability Conditions Factor Analysis

To measure the different dimensions of appropriability, as well as several other variables in our model, we are faced with both a problem and an opportunity. The problem results from the fact that we cannot measure these variables directly. The opportunity comes from the large number of potential measures that are available in the CMS. In order to both develop measures of the underlying unmeasured (latent) variables and to reduce the number of variables we have to deal with in our analyses, we used factor analysis to create new variables for the analysis. Factor analysis is a technique for extracting the underlying common factors (latent variables) that explain the correlations among a set of variables (Kim and Mueller, 1978). We can think of the correlations among several survey questions as resulting from their values being a result of a combination of one or more common factors and a unique, measure-specific component. Factor analysis is designed to discover how many common factors are needed to explain this set of correlations, and how strongly each measure is related to each of the underlying common factors (also called latent variables). We can think of factor analysis as trying to determine the rank of the correlation matrix (i.e., how many independent dimensions are in the matrix).

In the case of appropriability, we have a series of questions asking about the effectiveness of each of several mechanisms employed to protect product or process innovations.[12] The key mechanisms considered in our survey include secrecy, patents, other legal mechanisms (e.g., copyright or design registration), the exploitation of complementary manufacturing capabilities, that of complementary sales and service capabilities, and being first to market. Twelve measures of appropriability considered separately is rather cumbersome. More fundamentally, a priori, one might believe that each of these twelve measures need not reflect distinct appropriability strategies, but may

[12]We asked firms to rate the effectiveness of each of these mechanisms by indicating for product and process innovations separately the percentage of innovations for which each mechanism was judged to be effective in protecting the firm's competitive advantage from those innovations. The answer categories were: below 10%, 10-40%, 41-60%, 61-90%, and over 90%. These responses were then recoded to category midpoints. An important feature and limitation of this response scale is that it neither reflects use of mechanisms alone nor effectiveness of the mechanisms given use, but rather the product of the percentage of innovations for which a mechanism is used and the percentage of those innovations for which each mechanism is judged effective.

be related. Observation of the correlation matrix for the 12 items showed substantial correlations among groups of items (particularly between the product and process innovation items for the same mechanism). That possibility offers the potential for measure reduction. Accordingly, we conducted an exploratory factor analysis of the industry level data on the twelve measures to uncover the factor structure generating the correlations among the variables. This factor analysis generated three underlying variables (with eigenvalues greater than 1.0), and after orthogonal rotation (varimax), produced three distinct underlying variables, which we label CAPABILITIES/LEAD, LEGAL and SECRECY. Each mechanism measure loaded primarily on one of the three (the factorial complexity is one in each case), and each measure loaded at least .40 with its primary factor. Because of our interest in testing for differences in appropriability across industries, we redid the analysis at the individual level to generate standard errors around the industry mean scores for each factor. The factor analysis results presented in Table F1 show the factor loadings (the correlations between the measure and each factor) from the individual level analysis. The eigenvalues (also called the Sum of Squares) represent the strength of the factor in explaining the variation in each measure. They are calculated by summing the squares of the correlations of each measure with the underlying factor. Dividing this number by the number of measures produces the (average) variance explained (analagous to the R-square in an OLS regression). Presented in Table F1, the analysis yields a three factor solution breaking down into the following factors: 1. complementary capabilities and lead time (which explained the preponderance of variance in the correlation matrix); 2. legal mechanisms; and 3. secrecy.

[INSERT TABLE F1 ABOUT HERE]

The factor analysis suggests, therefore, that there are three distinct strategies that firms tend to use to protect their inventions: one involving the exploitation of complementary capabilities and lead time, another based on secrecy, and a third entailing the use of legal mechanisms, predominantly patents. Based on the factor analysis, we will operationalize appropriability in the form of effectiveness scores on each of these three distinct strategies and denote them, respectively, as CAPABILITIES/LEAD, LEGAL and SECRECY. Employing Bartlett's factor score (Mardia, Kent and Bibby [1979]), which uses the factor loadings on each measure as weights, we construct for each respondent normalized factor scores centered at zero and with a standard deviation of unity for each of the three factors.[13] To compute the factor score for each industry, we employ a simple average of each industry's respondent-level factor scores. We will

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[13] There are two important limitations to the factor analysis as currently implemented. First, we are treating all our raw measures as though they are continuous, although they are not; the response scales are categorical. Second, in conducting the initial factor analysis, we do not control for the multilevel character of the data, meaning that our procedure does not control for the fact that our respondents come from different industries. The reason for both of these limitations is that the state of the art in factor analysis itself has only recently begun to address these issues. See Johnson et al. [1999] for a more extensive treatment of these two issues.

repeatedly employ this same procedure for the other factor-based measures described below.

EXOGENOUS VARIABLES

Other factor indices include the following exogenous variables: INFO_UNIV, INFO_SUPPLIERS and MKT_CHANNELS.

Extraindustry Information Flows from Public Research:

Our survey offers numerous measures of the flows of public research to industrial R&D labs, where public research includes research conducted either in universities or government labs. The measures for the extraindustry knowledge flows originating from public research (i.e., universities and government labs and research institutes) are of two types. First, our survey offers various measures of the importance of public research to each firm's R&D. Second, we have indicators for the importance of the different channels through which this knowledge might be conveyed.

For our measure of the importance of public research to a firm's R&D, we construct a composite factor score reflecting three variables from the survey, including the reported frequency (rarely or never, semi-yearly, monthly, weekly, or daily; coded as 0 to 4) with which each responding R&D lab obtains "useful technical information" from universities or government research institutes, as well as the function of that information in either suggesting to each R&D lab new R&D projects or contributing to the completion of existing projects. Table F2 provides the factor loadings for these three measures reflecting the importance of university research in particular. These loadings provide the basis for constructing the variable denoted as INFO_UNIV.

[INSERT TABLE F2 ABOUT HERE]

To construct a variable that reflects the generic quality of the knowledge that underpins R&D within an industry, we exploit our subjective four-point Likert scale ratings of the importance of the contribution to industrial R&D of the channels of information on public research. The question was, "Below are some sources of information on the R&D activities or research findings of **universities or government research institutes and labs**. Please score each of the following in terms of that information's contribution to a **recently completed major project."** The answer categories were: not important, slightly important, moderately important, or very important (coded 1 to 4). The channels were: patents, publications and reports, public conferences and meetings, informal information exchange, recently hired graduates, licensed technology, joint or cooperative R&D projects, contract research, consulting and personnel exchanges. Presented in Table F3, the analysis yields three factors, that we broadly characterize as market-related channels (including contract research, joint and cooperative R&D, consulting, personnel exchanges, and recent hires), non market or "public" channels (including public conferences and meetings, publications and informal information exchange), and patent-related channels (including patents and licensed technology).[14] For our measure of the importance to an industry's R&D of generic knowledge, we use the factor score for the non-market or "public" channels, which we denote as UNIV_PUB.

[INSERT TABLE F3 ABOUT HERE]

Extraindustry Information Flows from Suppliers

We also considered the role of information originating from suppliers, and had five measures of the importance and nature of the impact of that information, including the frequency (e.g., weekly, monthly, etc.) of receiving useful technical information from suppliers, and whether information from independent or affiliated suppliers suggested new R&D projects or contributed to the completion of existing projects. Presented in F4, a factor analysis of these five measures yielded one factor. Denoted as INFO_SUPPLIERS, this measure is a normalized factor based index in which the factor loadings of these five measures are weights and the respondent-level scores are averaged to produce the industry scores.

[INSERT TABLE F4 ABOUT HERE]

Market Mediated Intraindustry Information Flows

Our measure of the extent of intraindustry information spillovers, INFO_RIVALS, has an important limitation, namely it reflects the effects of all information flows across rivals, and therefore might reflect market mediated as well as non-market mediated information flows. We are concerned, however, chiefly with non-market mediated flows, which should account for the preponderance of intraindustry nonpecuniary R&D spillover effects. We address this limitation of our measure of the dependent variable by including a control in our analyses for the extent of pecuniary information spillovers (i.e., information flows that are market mediated). We construct this control variable from our data on the channels through which firms learn about the R&D activities and innovations of their rivals. Specifically, we asked respondents to evaluate on a subjective four-point Likert scale the importance of different sources of information on rivals' R&D activities. The question was, "Below are some sources of information on the R&D activities or innovations of **other firms in your industry**.

[14] In the interest of parsimony, we tried to create a single indicator factor score combining all the measures in tables F2 and F3. However, this analysis did not produce a single factor solution. Instead, we find a four factor solution that largely reflects the factors presented in F2 and F3. Thus, while all these questions measure aspects of the influence of university research, they represent distinct dimensions and so we include both the influence of university research (INFO_UNIV) and the use of "public" channels (UNIV_PUB) to measure the influence of universities and government labs.

Please score each of the following in terms of the importance of that information's contribution to a **recently completed major project.**" The answer categories were: not important, slightly important, moderately important, or very important (coded 1 to 4). These sources include: patents, publications and reports, public conferences and meetings, informal information exchange, recent hires, licensed technology, joint or cooperative R&D ventures, contract research with other firms, the products of rivals (as through reverse engineering) and trade associations. As this list suggests, these channels are the sources of not only nonpecuniary but pecuniary R&D spillovers as well. We conducted a factor analysis of all these measures. Presented in Table F5, the factor loadings indicate two distinct groupings of information channels, corresponding to pecuniary and nonpecuniary channels, respectively. The first factor, reflecting the evaluations of the importance of information from public conferences and meetings, publications and reports and informal information exchange, partially reflect the effects of nonpecuniary (i.e., uncompensated) information flows. Reflecting respondents' evaluations of the importance of joint/cooperative R&D projects, licensed technology and contract research with other firms as sources of information on competitors' R&D, the second factor could be interpreted as a rough index of the effect of pecuniary spillovers. We use the factor score for the pecuniary channels, denoted as MKT_CHANNELS, to control for the importance of pecuniary spillovers in our intraindustry information flow equation.

[INSERT TABLE F5 ABOUT HERE]

A2. SINGLE INDICATORS

We also created several measures from single indicators. These include the following endogenous and exogenous variables.

ENDOGENOUS

R&D Information Flows

Our measure of the dependent variable, intraindustry R&D information flows, denoted as INFO_RIVALS, is drawn from our survey, and indicates the percentage of industry respondents indicating whether information from rivals suggested new R&D projects in the prior three years. [15]

[15] The Carnegie Mellon survey provides a number of measures of R&D related information spillovers across rivals. They include the frequency with which firms obtain useful technical information about the R&D activities of domestic rivals, the stage of the innovation process (i.e., project initiation, research stage, development stage, or commercialization) when firms tend to become aware of major R&D projects conducted by rivals, and the percentage of industry respondents (i.e., R&D lab managers) indicating that they received information from rivals that suggested new R&D projects or contributed to the completion of existing R&D projects, respectively. A factor analysis of

Innovative Effort

Innovative effort is constructed by employing a sales weighted average of the R&D intensities of the business units in each industry, where R&D intensity is business unit R&D divided by business unit sales. This variable is denoted as R&D_INTENSITY.

EXOGENOUS

Technological Rivals:

We operationalize this variable (TECH_RIVALS) with a survey measure of firms' reported estimates of "how many firms worldwide can introduce competing innovations in time to effectively diminish your firm's profits from your innovations." For this variable, we employ the median reported industry score.

Information from customers

To measure the contribution of information from customers (INFO_BUYERS), we use the percent of respondents reporting that information from customers suggested new R&D projects in the prior three years.

Product versus Process Innovation.

We also control for the mean percentage of R&D effort that focuses on new or improved products (versus new or improved processes) in each industry (PROD_R&D).

Cross-functional communication

To operationalize the strength of ties to other functions within the firm, we used the following survey item: "How frequently do your R&D personnel talk face-to-face with personnel from the following functions?" ("Marketing or Sales"; and "Production"). Frequency is measured as the mean of the categories of rarely or never, monthly, weekly or daily, which are represented as having values of one through four. We conducted a factor analysis on these two items but the single factor had a weak eigenvalue (less than 1.0) and so we treated each item separately. Since the former measure reflecting frequency of contact with sales or marketing never had any discernible effect, we only include our measure for the latter category, denoted as COMM_PRODN.

Importance of Reverse Engineering

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these four measures did not yield any factor with an eigenvalue greater than one.

At the risk of introducing some collinearity with our intraindustry information flow variable, INFO_RIVALS, we also believe that in some industries, the very nature of the technology can make secrecy less effective as a strategy. Specifically, innovations in some industries lend themselves more readily to reverse engineering. To capture this effect, we include a subjective four point Likert scale measure, drawn from the same survey question as MKT_CHANNELS (see above), of the importance to firms' R&D of information derived from rivals' products via, for example, reverse engineering. We denote this variable as REVERSE_ENGIN. We treat this variable as exogenous as it is likely to derive from the nature of the technology.

Importance of Recent Hires

To capture the effect of the movement of technical personnel as a source of information flows, we include a subjective four point Likert scale measure, drawn from the same survey question as MKT_CHANNELS (see above), of the importance to firms' R&D of information derived from recently hired technical personnel. We denote this variable as LABOR_MOBILITY.

Importance of University Science

To infer which underlying scientific or engineering fields are relevant to a given industry, we use a survey question which asks respondents to score on a subjective Likert scale the importance to their R&D of recent university or government research in each of seven fields of science and applied science.[16] After some empirical exploration, and reflecting the constraint imposed by a limited number of industry observations, we included the score for only that field which tends to be most closely associated with patenting, namely "medical and health science." This variable is denoted as MED_SCIENCE. In addition, to reflect the notion that the stronger is the underlying scientific knowledge base in general within an industry, the more patentable is the technology, we have included a measure, denoted as MAXSCI, which is the industry mean of the maximum scores obtained across the seven science and applied science fields.

Industry Demand

To control for the effect of industry demand, we also included a variable, SALES_GROWTH, which is constructed from Census of Manufactures data and reflects

[16] The question wording was: "How important to your R&D activities is the contribution of **university or government** research conducted over the last 10 years, by field of science and engineering?" The response categories were: not important, slightly important, moderately important, or very important; coded 1 to 4. The fields included were: biology, chemistry, physics, computer science, materials science, medical and health science, and mathematics.

each industry's average annual real rate of growth (percent change) in output between 1987 and 1992. While we would have also liked to include industry price and income elasticities, they are not available.

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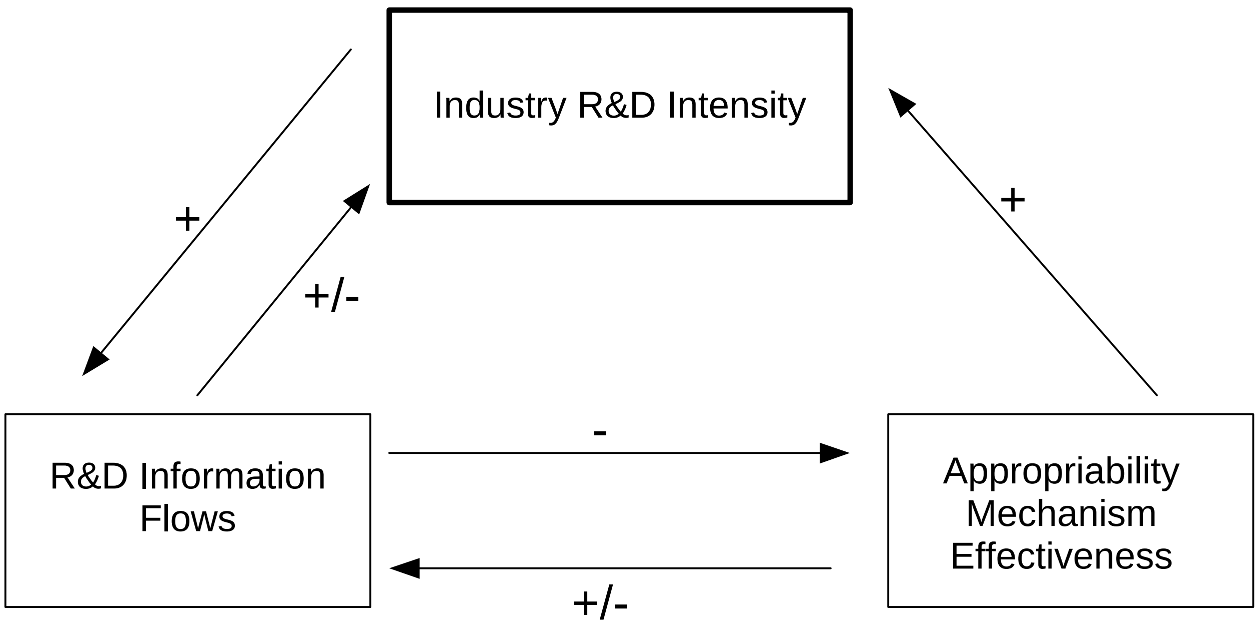

Diagram 1

Relationships across Industry R&D Intensity, Intraindustry R&D Information Flows and Appropriability Mechanism Effectiveness

Table 1. Descriptive Statistics for CMS sample

Variable	N	Mean	Median	1st Quartile	3rd Quartile
Business Unit Employees (1000's)	959	4.40	0.45	0.12	2.10
Business Unit Sales ($ millions)	833	1720.00	120.00	20.00	650.00
Firm Employees (1000's)	1115	20.00	3.30	0.30	17.00
Firm Sales ($ millions)	1129	4440.00	550.00	40.00	2750.00
Business Unit R&D Intensity (%)	700	2.33	1.92	0.67	4.61

Table 2. Variable list, with means and standard deviations for the 54 sample industries.

Variable Name	Measure	Mean	s.d.
CAPABILITIES/ LEAD	Factor index of extent to which complementary manufacturing and sales capabilities and being first are effective in protecting innovations	-.01	.38
LEGAL	Factor index of extent to which patents and other legal mechanisms are effective in protect innovations	-.02	.36
SECRECY	Factor index of extent to which secrecy is effective in protecting innovations	-.02	.49
INFO_RIVALS	Percent reporting information from rivals suggested new projects	43.3%	16.6
R&D_INTENSITY	Average industry R&D intensity	2.41%	2.65
MKT_CHANNELS	Factor index of market mediated information flows from competitors	-.02	.41
MAXSCI	Importance of university research from most relevant discipline (four point scale)	2.97	0.32
INFO_SUPPLIERS	Factor index of importance of information from suppliers	.04	.43
SALES_GROWTH	Average annual percent real growth in output, 1987 to 1992	-1.31%	2.41
TECH_RIVALS	Number of firms working on similar technologies	6.5	4.5
INFO_UNIV	Factor index of importance of information from universities and government labs.	-.04	.48
UNIV_PUB	Factor index of importance of public channels for accessing university research	-.03	.43
INFO_BUYERS	Percent reporting information from customers suggested projects	90.3%	8.75
PROD_R&D	Percent of R&D devoted to product innovation	66.7%	9.6
COMM_PRODN	Frequency of communication with manufacturing units (four point scale)	3.3	0.3
REVERSE_ENGIN	The importance of rivals' products as a source of information (four point scale)	2.3	0.4
LABOR_MOBILITY	The importance of recent hires as a source of information (four point scale)	1.9	0.2
MED_SCIENCE	The importance of university research in medical and health science (four point scale)	1.5	0.5

Note: The units for all factor indices are standardized deviations from the sample mean.

Table 3. Determinants of Industry R&D Intensity

Dependent Variable: R&D_INTENSITY

	Variable	OLS	2SLS	3SLS
		Regression Coefficients (standard error)		
1)	INTERCEPT	-4.219	-3.181	-3.210
		(3.087)	(3.704)	(3.044)
2)	MAXSCI	1.989[a]	0.855	0.054
		(1.093)	(1.352)	(1.085)
3)	INFO_RIVALS	0.043*	0.094**	0.146**
		(0.020)	(0.032)	(0.027)
4)	MKT_CHANNELS	-0.825	-1.547	-2.260*
		(0.762)	(0.928)	(0.911)
5)	INFO_SUPPLIERS	-2.163**	-2.373*	-2.888**
		(0.766)	(0.985)	(0.870)
6)	SALES_GROWTH	0.346**	0.286*	0.122
		(0.120)	(0.139)	(0.100)
7)	CAPABILITIES/LEAD	0.397	1.881	3.763*
		(0.886)	(1.794)	(1.658)
8)	LEGAL	1.579[a]	3.079*	4.511**
		(0.828)	(1.223)	(1.159)
9)	SECRECY	0.201	1.427	2.537*
		(0.750)	(1.188)	(1.072)
N		54	54	54
R-square		0.55	0.52	
F statistic		6.87**	6.16**	
R-squared FIRST STAGE			0.63	
BASMANN statistic			1.43	1.05
HAUSMAN statistic			4.22	

** Significant at the .01 confidence level

* Significant at the .05 confidence level

[a] Significant at the .10 confidence level

Table 4. Determinants of Intraindustry R&D Information Flow

Dependent Variable: INFO_RIVALS

	Variable	OLS	2SLS	3SLS
		Regression Coefficients (standard error)		
1)	INTERCEPT	22.762	8.516	15.500
		(17.230)	(21.678)	(15.685)
2)	SECRECY	-12.443	-16.369**	-19.097**
		(3.426)	(5.383)	(5.051)
3)	LEGAL	14.189**	3.487	-12.125
		(4.984)	(8.584)	(7.342)
4)	CAPABILITIES/LEAD	-0.771	-14.799	-24.596*
		(4.673)	(10.655)	(9.182)
5)	MKT_CHANNELS	0.282	7.273	13.368*
		(4.686)	(6.665)	(5.661)
6)	TECH_RIVALS	1.814**	1.429**	0.611
		(0.419)	(0.529)	(0.399)
7)	R&D_INTENSITY	1.427*	2.904**	4.262**
		(0.584)	(0.911)	(0.700)
8)	INFO_BUYERS	0.038	0.174	0.110
		(0.179)	(0.227)	(0.162)
9)	INFO_SUPPLIERS	3.373	9.752[a]	14.775**
		(4.045)	(5.561)	(4.970)
10)	UNIV_PUB	18.655**	16.844*	12.007*
		(5.305)	(6.520)	(4.817)
11)	INFO_UNIV	-5.572	-6.234	-5.181
		(4.270)	(4.921)	(3.706)
N		54	54	54
R-square		0.52	0.42	
F statistic		4.68**	3.13**	
R-squared FIRST STAGE			0.55	
BASMANN statistic			1.01	0.89
HAUSMAN statistic			3.96	

** Significant at the .01 confidence level

* Significant at the .05 confidence level

[a] Significant at the .10 confidence level

Table 5. Determinants of Appropriation Due to Secrecy

Dependent Variable: SECRECY

	Variable	Regression Coefficients (standard error) OLS	2SLS	3SLS
1)	INTERCEPT	2.198**	2.950**	3.180**
		(0.688)	(0.952)	(0.883)
2)	TECH_RIVALS	0.002	0.007	0.033
		(0.018)	(0.026)	(0.025)
3)	CAPABILITIES/LEAD	-0.158	0.301	0.682[a]
		(0.158)	(0.392)	(0.370)
4)	LEGAL	0.095	0.167	0.598[a]
		(0.200)	(0.360)	(0.334)
5)	PROD_R&D	-0.004	-0.011	-0.018*
		(0.006)	(0.008)	(0.008)
6)	INFO_RIVALS	-0.010*	-0.003	-0.006
		(0.004)	(0.009)	(0.008)
7)	REVERSE_ENGIN	-0.075	-0.233	-0.271
		(0.176)	(0.229)	(0.206)
8)	MKT_CHANNELS	0.512**	0.389	0.124
		(0.172)	(0.243)	(0.231)
9)	UNIV_PUB	0.786**	0.702**	0.732**
		(0.173)	(0.226)	(0.211)
10)	INFO_UNIV	-0.332*	-0.337*	-0.323*
		(0.149)	(0.166)	(0.156)
11)	LABOR_MOBILITY	-0.709**	-0.834*	-0.684*
		(0.254)	(0.332)	(0.303)
N		54	54	54
R-square		0.48	0.40	
F statistic		3.94**	2.92**	
R-squared FIRST STAGE			0.75	
BASMANN statistic			2.47*	1.86[a]
HAUSMAN statistic			1.43	

** Significant at the .01 confidence level

* Significant at the .05 confidence level

[a] Significant at the .10 confidence level

Table 6. Determinants of Appropriation Due to Complementary Capabilities and Lead Time

Dependent Variable: CAPABILITIES/LEAD

		Regression Coefficients (standard error)		
	Variable	**OLS**	**2SLS**	**3SLS**
1)	INTERCEPT	-2.481**	-2.453**	-1.983**
		(0.664)	(0.692)	(0.614)
2)	TECH_RIVALS	-0.026*	-0.022	-0.031*
		(0.012)	(0.014)	(0.013)
3)	SECRECY	-0.151[a]	-0.078	0.043
		(0.084)	(0.108)	(0.104)
4)	LEGAL	-0.359**	-0.292	-0.544**
		(0.126)	(0.179)	(0.156)
5)	INFO_RIVALS	0.002	0.001	-0.001
		(0.003)	(0.004)	(0.004)
6)	INFO_BUYERS	0.008[a]	0.008[a]	0.006
		(0.005)	(0.005)	(0.004)
7)	MKT_CHANNELS	0.502**	0.472**	0.494**
		(0.107)	(0.113)	(0.110)
8)	COMM_PRODN	0.327*	0.303*	0.225*
		(0.122)	(0.127)	(0.109)
9)	INFO_SUPPLIERS	0.172[a]	0.163[a]	0.105
		(0.090)	(0.096)	(0.079)
10)	PROD_R&D	0.011**	0.012**	0.014**
		(0.004)	(0.004)	(0.004)
N		54	54	54
R-square		0.48	0.43	
F statistic		4.52**	3.63**	
R-squared FIRST STAGE			0.43	0.61
BASMANN statistic			0.42	
HAUSMAN statistic			1.26	

** Significant at the .01 confidence level

* Significant at the .05 confidence level

[a] Significant at the .10 confidence level

Table 7. Determinants of Appropriation Due to Patent and Other Legal Mechanisms

Dependent Variable: LEGAL

	Variable	Regression Coefficients (standard error) **OLS**	**2SLS**	**3SLS**
1)	INTERCEPT	-1.279*	-1.564*	-1.277*
		(0.513)	(0.638)	(0.529)
2)	TECH_RIVALS	-0.048**	-0.044**	-0.050**
		(0.010)	(0.012)	(0.011)
3)	CAPABILITIES/LEAD	-0.341**	-0.671**	-0.725**
		(0.102)	(0.222)	(0.200)
4)	SECRECY	0.039	-0.028	0.172
		(0.098)	(0.175)	(0.146)
5)	INFO_RIVALS	0.008**	0.002	0.004
		(0.003)	(0.005)	(0.005)
6)	INFO_UNIV	0.053	-0.035	0.013
		(0.111)	(0.147)	(0.110)
7)	UNIV_PUB	-0.394**	-0.278	-0.338*
		(0.133)	(0.179)	(0.136)
8)	MAXSCI	0.174	0.262	0.156
		(0.172)	(0.221)	(0.172)
9)	MKT_CHANNELS	0.252*	0.363**	0.379**
		(0.101)	(0.131)	(0.120)
10)	PROD_R&D	0.008*	0.012*	0.013**
		(0.004)	(0.005)	(0.004)
11)	MED_SCIENCE	0.118	0.127	0.075
		(0.072)	(0.084)	(0.065)
N		54	54	54
R-square		0.58	0.48	
F statistic		5.87**	4.04**	
R-squared FIRST STAGE			0.66	
BASMANN statistic			1.35	1.32
HAUSMAN statistic			2.88	

** Significant at the .01 confidence level
* Significant at the .05 confidence level
[a] Significant at the .10 confidence level

Table F1

Factor Analysis of Respondent level Appropriability Mechanism Effectiveness Scores

Mechanism	Factor Loading		
	Factor 1 CAPABILI-TIES/LEAD	Factor 2 LEGAL	Factor 3 SECRECY
Product Manufacturing	**0.76**	-	-
Process Sales/Service	**0.73**	0.13	-
Process Manufacturing	**0.72**	-	-
Product Sales/Service	**0.66**	-	-
Process Being First to market	**0.53**	0.26	0.23
Process Complexity	**0.50**	0.16	0.32
Product Complexity	**0.46**	0.11	0.25
Product Being First to Market	**0.42**	0.18	0.25
Process Patents	**-**	**0.72**	0.10
Process Other Legal	0.28	**0.66**	-
Product Patents	-	**0.63**	0.11
Product Other Legal Mechanisms	0.22	**0.62**	0.10
Product Secrecy	0.13	**-**	**0.70**
Process Secrecy	0.12	0.17	**0.70**
Eigenvalue	3.15	1.19	1.31
Variance Explained	22.49%	13.65%	9.36%

Table F2

Factor Analysis of Respondents Scores on the Importance of Public Research

	Factor Loading
	Factor 1
Information Channel Function	INFO_UNIV
University or Government Labs – Suggested R&D Projects	**0.68**
University or Government Labs – Contributed to R&D Project Completion	**0.66**
Frequency of Interaction with North American Universities or Government Labs	0.32
Eigenvalue	1.26
Variance Explained	41.98%

Table F3

Factor Analysis of Respondent Scores on the Importance of Channels of Information Flow from Public Research (i.e., University or Government Labs)

		Factor Loading	
	Factor 1	Factor 2	Factor 3
Information Channel	Market	UNIV_PUB	Patent
Contract Research with Universities/Research Institutes	**0.71**	0.29	-
Joint/Cooperative R&D	**0.65**	0.29	0.23
Consulting with Individual Faculty/Researchers	**0.61**	0.39	0.14
Temporary Personnel Exchanges	**0.49**	0.21	-
Recently Hired Graduates with Advanced Degrees	**0.45**	0.23	0.23
Public Conferences and Meetings	0.26	**0.79**	0.15
Publications/Reports	0.21	**0.71**	0.36
Informal Information Exchange	0.37	**0.69**	0.12
Patents	0.14	0.26	**0.66**
Licensed Technology	0.40	-	**0.56**
Eigenvalue	2.15	2.04	1.09
Variance Explained	21.51%	20.30%	10.88 %

Table F4

Factor Analysis of Respondents Scores on the Importance of Suppliers

	Factor Loading
	Factor 1
Information Channel-Function	INFO_SUPPLIERS
Affiliated Suppliers – Suggested R&D Projects	**0.62**
Affiliated Suppliers – Contributed to R&D Project Completion	**0.61**
Independent Suppliers – Suggested R&D Projects	**0.46**
Independent Suppliers – Contributed to R&D Project Completion	**0.45**
Frequency of Interaction with North American Suppliers	0.32
Eigenvalue	1.26
Variance Explained	25.11%

Table F5

Factor Analysis of Respondent Scores on the Importance of Channels of Information Flow across Competitors

	Factor Loadings	
	Factor 1	Factor 2
Information Flows Channel	Nonmarket	MKT_CHANNELS
Public conferences and meetings	**0.74**	-
Publications/Reports	**0.71**	-
Informal information exchange	**0.45**	0.26
Trade Associations	0.36	0.17
Patents	0.24	0.16
Joint/Cooperative R&D Projects	0.17	**0.61**
Licensed Technology	0.22	**0.58**
Contract Research with Other Firms	-	**0.49**
Recently Hired Technical Personnel	0.19	0.34
Products (for example, by reverse engineering)	-	0.13
Eigenvalue	1.56	1.21
Variance Explained	15.64%	12.12%