INTER-INDUSTRY STRATEGIC R&D AND SUPPLIER-DEMANDER RELATIONSHIPS

Andrew C. Chang*

Abstract—This paper investigates if the R&D of an industry changes due to the R&D of an industry's suppliers and/or demanders. Using an annual industry-level panel of manufacturing R&D in the United States, I find that regressing the R&D of an industry on the lagged values of another industry's R&D suggests R&D comovement between industries with a strong supplier-demander relationship. Variance decompositions indicate that the R&D of an industry has high forecasting power over the R&D variance of another industry if the two industries share a strong supplier-demander relationship.

I. Introduction

TECHNOLOGICAL progress is essential for economic growth (Solow, 1957). However, there is reason to suspect that research and development (R&D) in the economy is at a level other than the social optimum (Arrow, 1962; Samuelson, 1954). The probable gap between the actual and social optimum levels of R&D, combined with the fact that R&D is a driver of economic growth, makes it crucial to understand how R&D decisions are made. This paper explores one possible determinant of R&D: how the R&D of an industry depends on that of the industry's suppliers and demanders.

The macroeconomic literature investigates several other possible causal factors of R&D. Researchers such as Barlevy (2007), Ouyang (2011), and Wälde and Woitek (2004) examine R&D's relation to the business cycle. Although this work offers different views on the mechanism by which R&D and the business cycle comove, the general consensus is that R&D is correlated to and possibly caused by business cycle fluctuations. Another strand of literature looks at the effectiveness of government subsidies or tax breaks on stimulating private R&D. This literature draws mixed conclusions. Bloom, Griffith, and Van Reenan (2002) and Lach (2002) conclude that public programs are effective at stimulating private R&D. Others, such as Goolsbee (1998), Wallsten (2000), and Wilson (2009), find contradictory results, up to the complete substitution of private R&D with public subsidies.[1]

The research supplements the existing literature by examining if the R&D of an industry depends on the R&D of other industries (industries behave strategically with respect to their R&D). I hypothesize the R&D of an industry will depend on the R&D of its upstream suppliers and/or its downstream demanders.

But why should supplier-demander relationships affect R&D?

First, two industries in a supplier-demander relationship should share both complementary or substitutable technologies and production processes. For example, the manufacturer Toyota actively cooperates with its suppliers to implement cost-minimizing, quality-maximizing technologies and production processes (Liker, 2004). Some of this cooperation even involves Toyota sharing its own methods with its suppliers to reduce their costs, resulting in a convergence of the supplier's technology with Toyota's. Because of the interrelation of technology between suppliers and demanders, the budget for R&D, money spent to develop these common products and processes, should also be interdependent between suppliers and demanders.[2]

Second, there may be some informational advantage of R&D activities between suppliers and demanders relative to other industry pairings. All else equal, industries could have better knowledge of the R&D strategies of their suppliers/demanders than of the R&D strategies of nonsuppliers/nondemanders. Because the R&D strategy of a supplier/demander directly affects an industry's profits, an industry should use this information when determining its own profit-maximizing level of R&D.

Third, interfirm partnerships are important in innovation (Powell & Grodal, 2006). For both the cost-sharing and informational reasons discussed, firms in a supplier-demander relationship can be expected to be collaborators in R&D projects.[3] Almost by definition, if a group of firms collaborates on an R&D project, then the R&D of one participating firm directly influences the R&D of the others. In the aggregate, these collaborations imply that many interfirm partnerships can drive inter-industry fluctuations of R&D.

For an example of strategic decision making by firms in interconnected industries, consider the Boeing 787, a

Received for publication October 15, 2010. Revision accepted for publication August 9, 2011.

* University of California, Irvine.

This research was generously supported by a grant from the Department of Economics at the University of California-Irvine. However, the university and its affiliates had no influence on the content of this research. I am particularly indebted to Linda R. Cohen and Min Ouyang for reading and critiquing numerous drafts of this paper. I have also received and gratefully acknowledge assistance and helpful comments from William A. Branch, Jiawei Chen, Amihai Glazer, Ivan Jeliazkov, David Licata, Alicia Lloro, Michael McBride, David Neumark, Dale J. Poirier, George C. Saioc, James Tierney, Raymond Wolfe, Cathy Zhang, Guoxiong Zhang, an anonymous referee, and participants at the University of California-Irvine Department of Economics poster session. Matt Bidart and Serena Quach were instrumental in assisting me with presenting this research. Any errors are mine.

A supplemental appendix is available online at http://www.mitpressjournals.org/doi/suppl/10.1162/REST_a_00273.

[1] Microeconomic studies also look at topics such as, but not limited to, absorptive capacity (Cohen & Levinthal, 1989), liquidity constraints (Himmelberg & Petersen, 1994), and patent and technology races (Lerner, 1997). For an overview, see Hall and Rosenberg (2010).

[2] More generally, cost reduction can be explained by the existence of R&D spillovers (externalities) between supplying and demanding industries. Spillovers between industries can cause their R&D spending decisions to be interrelated (Harhoff, 1996).

[3] These are only two of many possible reasons that firms would want to cooperate in R&D. Others include access to economies of scale and risk sharing (Becker & Dietz, 2004).

revolution in commercial aviation as the first commercial airplane primarily constructed from composite material instead of aluminum (Norris et al., 2005). When aircraft manufacturer Boeing decided to build the 787, a substantial portion of engineering work suited for aluminum-based aircraft became obsolete. An enormous increase in R&D by Boeing was required to redesign parts and systems for a composite-based aircraft. This increase in R&D funded materials testing, computer modeling, and specification gathering, among other things. As Boeing contracted out parts of the design, Boeing's suppliers, including Mitsubishi Heavy Industries, Toray Industries, Honeywell, and Rockwell-Collins, responded by increasing their R&D to produce new products and processes compatible with the 787. Boeing's suppliers made strategic decisions to increase their R&D as a response to Boeing's initial increase in R&D.

Based on Shea (1991) and using input-output tables, I measure the strength of supplier-demander relationships between industries with the direct link. The construction of the 787 can illustrate the concept of the direct link. Mitsubishi Heavy Industries, one of the companies Boeing contracted to build the 787's wings, is directly linked to Boeing: Boeing's 787 uses parts manufactured by Mitsubishi Heavy Industries. The components from Mitsubishi are directly used by Boeing; there is no intermediary. I expect that Mitsubishi Heavy Industries, which is directly linked to Boeing, considers Boeing's R&D decisions when it is deciding on its own R&D budget and vice versa.

Using Granger causality tests, I find regressing the R&D of an industry on the lagged values of another industry's R&D generates economically and statistically significant coefficients if the industries share a strong direct link. This result is robust to controlling for different lag structures, different estimators, possible measurement error, government tax credits, and both aggregate and industry-specific business cycles. Variance decompositions indicate the R&D of an industry that has higher forecasting power over the R&D variance of another industry if the two industries share a strong direct link. If the two industries share a weak direct link, the inter-industry R&D forecasting power is lower. This finding is robust to using different identification schemes. Taken together, the Granger causality tests and variance decompositions imply a strong supplier-demander relationship between two industries is associated with increased interconnectedness of their R&D.

Section II describes the data and further elaborates on the direct link. Section III discusses the model and estimation procedure. Section IV presents the results and section V concludes.

II. Data

The data on company-financed U.S. R&D come from the National Science Foundation's (NSF) Industrial Research and Development Information System (IRIS), as well as the NSF's Survey of Industrial Research and Development for 2005 (NSF, 2009, & 2010). The data are a panel of annual observations from manufacturing industries described at the two-, three-, or four-digit 1987 Standard Industry Classification (SIC) level between 1956 and 1998. While data are available for 1999 to 2007, data from 1999 to 2007 were collected according to the North American Industry Classification System (NAICS). The change in industrial classification system makes the data from 1956 to 1998 incomparable to the data from 1999 to 2007. Therefore, this analysis focuses on 1956 to 1998 to maximize the time-series dimension of the data: the same approach as in Ouyang (2011). I convert company-financed R&D from nominal dollars to real-year 2005 dollars with the Bureau of Economic Analysis (BEA) chain-type price index (BEA, 2011). The implicit price deflator gives similar results.

In the NSF R&D panel, some industries are missing observations. The NSF censors observations if disclosure of an industry's R&D expenditures gives public information about a single firm's R&D expenditures. Seven two- or three-digit SIC industries have a full panel of company-financed R&D available. I use the industries where a full panel is available and group the remainder of R&D spending into an "all other" category. Therefore, the industries I analyze are SIC 28 (Chemicals), 33 (Primary Metals), 34 (Fabricated Metals), 35 (Machinery), 36 (Electrical Equipment), 372 and 376 (Aircraft and Missiles), 38 (Scientific Instruments), and the All Other industry (various two-digit SIC industries). This setup allows the maximum cross-sectional dimension while still using the full time period of 1956 to 1998 and includes 100% of company-financed R&D in the analysis.

The BEA's input-output tables capture the inter-industry flow of goods and labor and are described by Lawson (1997). The BEA publishes the input-output tables once every five years. The 1992 version of these tables is based on the 1987 SIC classification. Because the NSF R&D data are also classified according to the 1987 SIC classification, I use the 1992 version of the input-output tables to measure inter-industry linkages.[4]

Following Shea (1991), I use the BEA's tables to create a measure of inter-industry linkage: the direct demand share matrix (table 1). Appendix A, in the online supplement, provides a detailed construction of the direct demand share matrix.

In table 1, row i, column j is the share of direct demand for industry i coming from industry j. The direct demand share matrix shows the strength of supplier-demander relationships with larger entries indicating a stronger relationship. For example, from table 1, we can see industry 28 (Chemicals) is mostly independent of other industries. Aside from its

[4] A potential concern in measuring inter-industry linkages is that a single year's input-output tables fails to capture possible changes over time. Unfortunately, input-output tables older than 1982 are coded under alternative versions of the SIC and are not directly comparable to the newer tables. However, as a robustness check, I use the 1987 version of the input-output tables to calculate the inter-industry links. The links are relatively consistent between these two versions of the input-output tables and produce similar results.

TABLE 1.—DIRECT DEMAND SHARE MATRIX

Industry Description	Supplying Industry	Demanding Industry							
		28	33	34	35	36	37	38	Various
Chemicals	28	0.23	0.01	0.01	0.00	0.01	0.00	0.01	0.40
Primary Metals	33	0.00	0.24	0.26	0.14	0.07	0.02	0.02	0.24
Fabricated Metals	34	0.02	0.01	0.08	0.08	0.05	0.02	0.02	0.61
Machinery	35	0.01	0.03	0.02	0.23	0.03	0.02	0.02	0.46
Electrical Equipment	36	0.00	0.00	0.00	0.10	0.17	0.02	0.06	0.34
Aircraft and Missiles	37	0.00	0.00	0.00	0.00	0.00	0.33	0.00	0.05
Scientific Instruments	38	0.00	0.00	0.00	0.01	0.02	0.07	0.05	0.29
All Other	Various	0.01	0.01	0.00	0.01	0.01	0.00	0.00	0.44

This matrix captures the direct link between industries. This table describes Aircraft and Missiles (SIC 372, 376) as SIC 37 for simplicity of notation. Entry *ij* (row *i*, column *j*) is the fraction of direct demand for industry *i* by industry *j*.

demand for itself and the All Other industry, all of the entries in the matrix for industry 28 are small, which indicates it does not supply goods to or demand goods from the other industries. At the same time, industry 33 (Primary Metals) is closely related to industries 34 (Fabricated Metals) and 35 (Machinery). The direct demand shares between these industries are relatively large.

In the last column of table 1, the demand shares for the aggregated All Other industry are all relatively large. This result comes naturally from adding the output of multiple two-digit SIC industries into a single category.

A specific example of direct demand: part of industry 34's production is nameplates, both engraved and etched. These nameplates can be sold to and used by industry 35 as identifiers for machines, such as trucks or tractors. The nameplates from industry 34 are used directly as a component for industry 35's trucks and tractors.

III. Model and Estimation

This paper estimates multiple specifications of equation (1):

$$RD_{j,t} = \mu_j + \sum_{i=1}^{N} B(L)RD_{i,t} + A(L)X_{j,t} + \varepsilon_{j,t};$$
$$\forall j = 1, \ldots, N, \forall t = 1, \ldots, T, \tag{1}$$

where j is an industry, N is the total number of industries, t is the year, RD is company-financed R&D, X is a matrix of control variables, $A(L)$ and $B(L)$ are lag polynomials, and ε is the error. I estimate equation (1) as a seemingly unrelated regression (Zellner, 1962). Estimation with equation-by-equation ordinary least squares gives similar results.[5] I model equation (1) using two lags for $B(L)$. Similar results hold using one lag or one lag and contemporaneous R&D, $i \neq j$.

I model inter-industry R&D comovement with the specification of equation (1) because I expect that if R&D comovement between industries driven by supplier-demander relationships exists, it will appear with a lag. This expectation is for two reasons. First, if industries use superior information about the R&D expenditures of suppliers or demanders to determine their own profit-maximizing level of R&D, then this reaction should be lagged. Information on R&D expenditures takes time to disseminate between industries. Second, short-run frictions may necessitate delayed strategic adjustments of R&D expenditures. For example, firms that wish to increase R&D expenditures by hiring additional scientists and engineers must search the labor market and screen potential matches. This search and matching process takes time. Therefore, firms may only be able to strategically adjust their salaries for R&D workers with a lag. In the aggregate, this delay implies that industry-level adjustments of R&D expenditures should appear with a lag.

Equation (1) uses the first differenced natural log levels of both RD and the controls in X. Therefore, the estimated coefficients represent elasticities of R&D. This transformation is used for two reasons. First, it makes the nonstationary variables covariance stationary as supported by unit root tests. Second, it removes any unobserved, industry-specific, time-invariant effects that might be correlated with the error term and cause inconsistent estimation. Therefore, after differencing and taking lags into account, the effective time period of estimation for equation (1) is 1959 to 1998, giving 320 industry-year observations.

To test if the R&D of an industry depends on the lagged R&D of other industries, I use the Granger causality test of Granger (1969). The null hypothesis of this test is there is no Granger causal relationship between the R&D of two industries (the coefficients for $RD_{i,t}$ are 0). The alternative hypothesis is there exists a Granger causal relationship.

The matrix X contains controls for the U.S. R&D tax credit, a NSF R&D survey design change, aggregate and industry-specific output, and aggregate and industry-specific government-financed R&D to eliminate possible endogeneity. Appendix B, in the online supplement, describes the data sources for and the detailed construction of the controls.

IV. Results and Discussion

A. Granger Causality Results

This section reports the estimation results of equation (1) and links the estimation results to the direct demand shares in

[5] All unreported results are available on request.

TABLE 2.—GRANGER CAUSALITY WITH INDUSTRY-SPECIFIC CONTROLS

	Dependent Variable							
	$RD_{28,t}$	$RD_{33,t}$	$RD_{34,t}$	$RD_{35,t}$	$RD_{36,t}$	$RD_{37,t}$	$RD_{38,t}$	$RD_{AO,t}$
$RD_{28,t-1}$	0.24	−0.06	0.24	−0.94	0.73	0.26	0.01	0.16
$RD_{28,t-2}$	−0.24	0.30	1.11	−0.12	0.32	0.40	0.17	0.10
	(0.45)	(0.86)	(0.02)**	(0.09)*	(0.12)	(0.75)	(0.82)	(0.86)
$RD_{33,t-1}$	0.12	0.07	−0.46	0.02	−0.16	0.52	−0.10	0.20
$RD_{33,t-2}$	0.19	−0.58	−0.67	−0.22	0.04	0.05	−0.04	−0.23
	(0.14)	(0.09)*	(0.00)***	(0.56)	(0.67)	(0.15)	(0.61)	(0.27)
$RD_{34,t-1}$	0.02	−0.12	−0.78	−0.23	0.11	−0.31	−0.06	−0.15
$RD_{34,t-2}$	0.04	0.00	−0.05	−0.19	0.19	−0.27	0.20	−0.10
	(0.94)	(0.90)	(0.00)***	(0.46)	(0.54)	(0.50)	(0.15)	(0.59)
$RD_{35,t-1}$	0.03	0.30	0.54	0.32	0.10	0.16	−0.07	0.32
$RD_{35,t-2}$	0.11	0.11	0.22	−0.25	0.08	−0.44	0.09	−0.17
	(0.48)	(0.27)	(0.00)***	(0.15)	(0.58)	(0.34)	(0.70)	(0.06)*
$RD_{36,t-1}$	0.03	0.12	0.59	0.56	0.02	0.62	0.05	0.04
$RD_{36,t-2}$	−0.02	−0.08	0.52	0.36	−0.22	0.21	0.09	−0.06
	(0.97)	(0.91)	(0.00)***	(0.01)***	(0.68)	(0.12)	(0.79)	(0.94)
$RD_{37,t-1}$	0.03	0.31	−0.27	0.02	0.13	−0.13	−0.01	−0.09
$RD_{37,t-2}$	−0.05	−0.10	−0.26	−0.16	0.10	0.06	−0.03	−0.07
	(0.79)	(0.31)	(0.04)**	(0.54)	(0.53)	(0.82)	(0.95)	(0.65)
$RD_{38,t-1}$	0.06	−0.28	0.87	−0.84	0.42	0.42	0.04	0.30
$RD_{38,t-2}$	−0.35	0.03	1.32	0.02	0.34	0.24	0.15	0.07
	(0.26)	(0.83)	(0.00)***	(0.07)*	(0.37)	(0.72)	(0.82)	(0.54)
$RD_{AO,t-1}$	−0.33	−0.44	−0.54	0.82	−0.76	0.54	0.14	0.01
$RD_{AO,t-2}$	0.25	−0.70	−0.58	−0.54	0.09	0.56	−0.22	0.08
	(0.31)	(0.18)	(0.03)**	(0.09)*	(0.09)*	(0.30)	(0.71)	(0.96)

The model is $RD_{j,t} = \mu_j + \sum_{i=1}^{N} B(L)RD_{i,t} + A(L)X_{j,t} + \varepsilon_{j,t}$. RD is company-financed R&D. The control matrix, $X_{j,t}$, consists of industry j's output, government-financed R&D for industry j, the control for the 1981 R&D tax credit, and the control for the NSF's R&D survey design change. The estimated control coefficients are not reported to conserve space. This table describes Aircraft and Missiles (SIC 372, 376) as SIC 37 for simplicity of notation and the All Other industry as AO. The real natural log of all variables is first differenced. The time period of estimation after differencing and taking lags into account is 1959 to 1998, giving 320 industry-year observations. p-values of F-tests of joint significance for $RD_{j,t-l}$ in parentheses. Significant at ***1%, **5%, and *10%. Number of observations: 320.

table 1. The main result is regressing the R&D of industry i on the lagged R&D of industry j indicates stronger patterns of inter-industry R&D comovement between industries that also have larger direct demand shares (share a stronger supplier-demander relationship). For brevity, this subsection displays the estimation results of equation (1) for two models with representative sets of controls. The results are robust across several different sets of controls.

Table 2 presents the estimation results using a set of industry-specific controls and several results emerge. First, the R&D of an industry only Granger-causes a its own R&D in two cases. Second, the R&D of the All Other industry exhibits a relatively small Granger causal impact on the R&D of the disaggregated two- or three-digit SIC industries, given how large its demand shares are. For example, at the 5% level the R&D of the All Other industry only Granger-causes the R&D of industry 34 (Fabricated Metals). Third, for the disaggregated industries, three of the four industries with the strongest supplier-demander relationships also exhibit a Granger causal relationship between their R&D. In addition, the coefficient magnitudes are economically significant. These results suggest between the disaggregated industries, a strong supplier-demander relationship results in comoving R&D. The results are less clear on the aggregated All Other industry and on intra-industry R&D.

Of the control variables, unreported to save space, industry-specific output has the strongest effect on R&D. Government-financed R&D is statistically and economically significant for industries 28 (Chemicals), 35 (Machinery), and 36 (Electrical Equipment). The controls for the R&D tax credit and the NSF's 1991 survey design change are small in magnitude and largely insignificant.

Table 3 presents the estimation results from a specification using a set of aggregate controls. The results are similar to the model in table 2 with industry-specific controls. Here again, the Granger causality results suggest between the disaggregated industries, industries with strong supplier-demander relationships also have interrelated R&D. The results for within-industry R&D and the All Other industry are unclear. The aggregate controls tend to have larger point estimates than the industry-specific controls, although they are estimated with less precision. Taken as a whole, only contemporaneous aggregate output is significant.

The evidence indicates inter-industry R&D comovement between the disaggregated industries. However, so far the association between the Granger causality tests and the direct demand shares of table 1 has been by informal observation. To add analytical rigor to the relationship between the Granger causality results and the input-output links, I estimate the probit model in equation (2) and the linear probability model in equation (3) with maximum likelihood.

$$\begin{aligned} &Pr(Gcause_{i,j} = 1|DDS) \\ &\quad = \Phi(\alpha + \beta \max(DDS_{i,j}, DDS_{j,i})D_{Inter} \\ &\qquad + \gamma \max(DDS_{i,j}, DDS_{j,i})D_{Intra}), \end{aligned} \tag{2}$$

$$\begin{aligned} &Pr(Gcause_{i,j} = 1|DDS) \\ &\quad = \delta + \eta \max(DDS_{i,j}, DDS_{j,i})D_{Inter} \\ &\qquad + \theta \max(DDS_{i,j}, DDS_{j,i})D_{Intra} + \nu_{i,j}. \end{aligned} \tag{3}$$

TABLE 3.—GRANGER CAUSALITY WITH AGGREGATE CONTROLS

	Dependent Variable							
	$RD_{28,t}$	$RD_{33,t}$	$RD_{34,t}$	$RD_{35,t}$	$RD_{36,t}$	$RD_{37,t}$	$RD_{38,t}$	$RD_{AO,t}$
$RD_{28,t-1}$	0.27	−0.17	−0.29	−0.68	0.18	0.44	−0.03	0.27
$RD_{28,t-2}$	0.29	0.03	−0.17	−0.14	−0.40	−0.15	0.27	0.38
	(0.25)	(0.95)	(0.80)	(0.38)	(0.51)	(0.76)	(0.67)	(0.37)
$RD_{33,t-1}$	−0.10	−0.04	−0.20	0.76	0.20	0.69	0.06	−0.14
$RD_{33,t-2}$	0.07	−0.13	−0.66	−0.81	0.02	−0.19	0.02	−0.12
	(0.69)	(0.86)	(0.01)***	(0.01)***	(0.49)	(0.11)	(0.88)	(0.31)
$RD_{34,t-1}$	0.13	0.22	−0.73	−0.85	0.02	−0.57	−0.07	−0.05
$RD_{34,t-2}$	0.03	0.07	−0.03	−0.72	0.02	−0.49	0.10	0.11
	(0.62)	(0.81)	(0.05)**	(0.01)***	(0.99)	(0.15)	(0.64)	(0.66)
$RD_{35,t-1}$	−0.02	0.20	0.58	0.59	0.21	0.32	−0.03	0.09
$RD_{35,t-2}$	0.09	0.15	−0.15	−0.36	−0.42	−0.31	0.11	−0.01
	(0.56)	(0.30)	(0.02)**	(0.04)**	(0.05)**	(0.48)	(0.67)	(0.75)
$RD_{36,t-1}$	−0.06	−0.07	0.93	0.43	0.51	0.46	−0.03	−0.02
$RD_{36,t-2}$	−0.02	−0.32	0.05	1.06	−0.32	0.35	0.09	0.00
	(0.87)	(0.65)	(0.01)***	(0.01)***	(0.06)*	(0.31)	(0.90)	(0.99)
$RD_{37,t-1}$	−0.07	0.40	0.10	−0.28	0.24	−0.21	−0.03	−0.12
$RD_{37,t-2}$	−0.06	−0.03	−0.08	−0.33	0.11	0.05	−0.06	−0.04
	(0.58)	(0.18)	(0.73)	(0.08)*	(0.23)	(0.67)	(0.82)	(0.60)
$RD_{38,t-1}$	0.04	−0.99	0.12	0.60	−0.23	1.09	0.17	0.25
$RD_{38,t-2}$	−0.12	−0.28	0.17	1.35	−0.09	0.46	0.41	−0.12
	(0.74)	(0.14)	(0.88)	(0.00)***	(0.79)	(0.16)	(0.20)	(0.53)
$RD_{AO,t-1}$	−0.54	−0.55	0.33	0.91	−0.09	0.60	−0.01	0.15
$RD_{AO,t-2}$	0.30	−0.87	−0.29	−0.11	0.19	1.24	−0.24	−0.18
	(0.07)*	(0.05)**	(0.76)	(0.17)	(0.89)	(0.02)**	(0.65)	(0.82)

This table reports estimates of $RD_{j,t} = \mu_j + \sum_{i=1}^{N} B(L)RD_{i,t} + A(L)X_{j,t} + \varepsilon_{j,t}$. RD is company-financed R&D. The control matrix, $X_{j,t}$, consists of one lag, contemporaneous, and one lead of aggregate output as well as one lag, contemporaneous, and one lead of aggregate government-financed R&D. The estimated control coefficients are not reported to conserve space. This table describes Aircraft and Missiles (SIC 372, 376) as SIC 37 for simplicity of notation and the All Other industry as AO. The real natural log of all variables is first differenced. The time period of estimation after differencing and taking lags into account is 1959 to 1998, giving 320 industry-year observations. p-values of F-tests of joint significance for $RD_{j,t-l}$ in parentheses. Significant at ***1%, **5%, and *10%. Number of observations = 320.

In equations (2) and (3), i and j are industries, $\Phi(\bullet)$ is the standard normal cumulative distribution function, $Pr(\bullet)$ is probability, $DDS_{i,j}$ is the entry in row i, column j of the direct demand share matrix (direct demand for industry i by industry j), and ν is the error. D_{Inter} is a dummy variable for when the observation represents an inter-industry link ($i \neq j$), and D_{Intra} is a dummy variable for when the observation is an intra-industry link ($i = j$). The dependent variable, $Gcause_{i,j}$, is a binary variable indicating whether there is a Granger causal relationship between industry i and industry j. This formulation means $Gcause_{i,j}$ equals 1 if industry i Granger causes industry j's R&D or vice versa. Therefore, in the probit model, β represents the impact of a stronger inter-industry link on the probability of inter-industry R&D comovement and γ represents the impact of a stronger intra-industry link on the probability of intra-industry R&D comovement. In the linear probability model, the analogous parameters are η for inter-industry links and θ for intra-industry links.

The intuition behind equations (2) and (3) is as follows: a stronger link between two industries i and j, measured as either $DDS_{i,j}$ (i is the supplier, j is the demander) or $DDS_{j,i}$ (j is the supplier, i is the demander) should result in an increased probability of finding a Granger causal result between these two industries. I estimate separate effects of the direct demand shares on inter-industry and intra-industry R&D because there are different drivers of intra-industry R&D (such as patent races or absorptive capacity) than for inter-industry R&D. Therefore, I anticipate the effect of input-output links on inter-industry R&D comovement should be different from that on intra-industry R&D comovement.

Ideally I would also be able to differentiate between the effects of having a strong supplier relationship versus a strong demander relationship. Unfortunately, the R&D data lack sufficient detail to identify the effect of a strong supplier relationship separately from a strong demander relationship. The correlation between having a stronger demander relationship and a stronger supplier relationship is greater than 0.95. However, I can test if there exists a strong supplier or demander relationship between two industries if there also exists a Granger causal relationship between their R&D. Because I hypothesize that inter-industry links contribute to inter-industry R&D comovement, I expect both β and η to be positive (the coefficients for inter-industry comovement). Also, because intra-industry R&D comovement is potentially driven by different factors, the sign of δ and θ is unclear (the coefficients for intra-industry comovement).

Table 4 shows the estimation results of equations (2) and (3). It defines a Granger causal relationship as significant at the 5% level. Defining the relationship at the 1% level decreases the magnitude of the estimates for the model with aggregate controls, but the signs of the coefficients remain the same. The 1% definition gives similar results for the model with industry-specific controls. Defining the relationship at the 10% level gives similar results for both models.

In panels A and B of table 4, column 1 uses the full sample and column 2 excludes the All Other industry. When using

TABLE 4.—ASSOCIATING GRANGER CAUSALITY TO DIRECT DEMAND SHARE MATRIX

	Coefficient	(1)	(2)
A. Estimation of Probit Model in Equation (2)			
Industry-specific controls	$\hat{\beta}$	0.15	2.24
		(0.72)	(0.05)**
	$\hat{\gamma}$	−1.51	−1.19
		(0.06)*	(0.12)
Aggregate controls	$\hat{\beta}$	−0.13	5.26
		(0.75)	(0.00)***
	$\hat{\gamma}$	−0.59	0.78
		(0.40)	(0.28)
Excluded industry			All Other
Number of observations		36	28
B. Estimation of Linear Probability Model in Equation (3)			
Industry-specific controls	$\hat{\eta}$	0.22	2.67
		(0.69)	(0.03)**
	$\hat{\theta}$	−0.78	−0.71
		(0.04)**	(0.14)
Aggregate controls	$\hat{\eta}$	−0.11	4.45
		(0.77)	(0.00)***
	$\hat{\theta}$	−0.49	0.56
		(0.35)	(0.50)
Excluded industry			All Other
Number of observations		36	28

Industry-specific controls refers to the model in table 2 and aggregate controls represents the model in table 3. The estimates of panels A and B are the average marginal effect of a 1% increase in the direct demand share on the percentage probability of a Granger causal relationship between two industries' R&D. $\hat{\beta}$ and $\hat{\eta}$ are the estimates for inter-industry links. $\hat{\gamma}$ and $\hat{\theta}$ are the estimates for intra-industry links. Standard errors are robust to heteroskedasticity. p-values of t-tests are reported in parentheses. Significant at ***1%, **5%, and *10%.

the full sample in column 1, the coefficients for inter-industry comovement are small and insignificant. For intra-industry comovement, there is some evidence that weaker intra-industry links are associated with stronger comovement of intra-industry R&D. However, this pattern is not robust to different control schemes, so the evidence indicating input-output links is inversely related to intra-industry comovement of R&D are weak at best.

When excluding the All Other industry in column (2), the results for inter-industry links become clearer. The estimates for inter-industry links are all the anticipated sign (positive) and are statistically significant. They imply a 1% increase in the direct demand share between two industries increases the probability of finding a Granger causal relationship by 2% to 5%. These models give strong support for the notion inter-industry links are associated with inter-industry comovement of R&D, at least between the disaggregated two- or three-digit SIC industries. These results are consistent with the casual observations made about the original estimation results in tables 2 and 3. The All Other industry, while having relatively large direct demand shares, lacks a consistent Granger causality pattern between its R&D and the R&D of the remaining industries. This pattern could be because the All Other industry is composed of many two-digit SIC industries as opposed to either a single two-digit SIC or a combination of three-digit SICs. In contrast, between industries where disaggregated R&D data are available, there seems to be R&D comovement between industries that also share strong input-output links.

The evidence in tables 2 and 3 implies the R&D of industries fluctuates in response to the R&D of other industries. In addition, the estimates from table 4 demonstrate this comovement pattern is related to the strength of the supplier-demander relationship between industries.

B. *Variance Decomposition Results*

To further analyze inter-industry R&D comovement, this section presents the results from long-run variance decompositions of the model with aggregate controls in table 3. The variance decompositions indicate that the R&D of an industry has high long-run forecasting power over the R&D variance of another industry if the two are linked with a strong supplier-demander relationship. The forecasting power drops as the supplier-demander relationship weakens. This finding is robust to different identification schemes.

The reasoning behind using variance decompositions is as follows: if an industry is making R&D decisions taking into account the R&D of its suppliers and/or demanders, then the R&D of its suppliers and/or demanders should explain a larger portion of the variance of the industry's R&D relative to nonsuppliers and nondemanders. Table 5 shows the results of the variance decompositions.

An issue with constructing variance decompositions is the set of identification restrictions to use. Fortunately, two reasonable sets of Cholesky restrictions fit with the strategic R&D hypothesis of this paper. Because I hypothesize that inter-industry links are a driving force behind R&D fluctuations, I construct the first order as the industries with the strongest to the weakest inter-industry links and place the All Other industry last in the order. A shock to a relatively more interconnected industry should have a stronger contemporaneous effect on other industries, so it is placed earlier in the order (with the most interconnected industry first in the order). Analogously, a shock to a less interconnected industry should have a minimal contemporaneous effect on other industries and is placed later in the order. I place the All Other industry last because I expect this pattern to be stronger between the industries at the two- or three-digit SIC level. Therefore, the first Cholesky order is industry 33, industry 34, industry 35, industry 36, industry 38, industries 372 and 376, industry 28, and All Other.

However, you could argue that by ordering the restrictions from strongest to weakest inter-industry links, the results will be biased in favor of finding a pattern between inter-industry links and R&D expenditures. Therefore, for the second order, I use the exact opposite order of the first: industries from the weakest to the strongest inter-industry links, with the All Other industry first in the order. This second order should, if anything, bias the variance decomposition against finding that supplier-demander relationships affect R&D.

Panel A in table 5 shows the variance decomposition results using the first identification order. The first row is the variance industry 28 explains about other industries, the second row is the variance industry 33 explains about other

TABLE 5.—VARIANCE DECOMPOSITIONS OF MODEL WITH AGGREGATE CONTROLS

	Dependent Variable								Total Inter-industry Variance
	$RD_{28,t}$	$RD_{33,t}$	$RD_{34,t}$	$RD_{35,t}$	$RD_{36,t}$	$RD_{37,t}$	$RD_{38,t}$	$RD_{AO,t}$	
A. First Cholesky Order, Strongest to Weakest Inter-industry Links									
$RD_{28,t}$	48.1***	3.1	0.5	2.2	2.1	5.5	3.4	17.6	34.4
$RD_{33,t}$	5.0	35.4*	8.8	13.5	21.2	8.4	4.9	16.6	78.4
$RD_{34,t}$	2.6	9.8	34.1**	10.2	6.6	5.1	6.8	8.9	50.0
$RD_{35,t}$	8.5	22.1	24.5*	35.2**	31.0**	5.8	6.6	3.7	102.2
$RD_{36,t}$	3.2	1.9	4.4	2.3	20.3**	4.5	2.0	3.2	21.5
$RD_{37,t}$	5.3	11.7	10.8	14.3	10.9	36.3**	3.4	7.5	63.9
$RD_{38,t}$	6.7	4.8	4.8	4.1	3.4	21.5**	65.5**	2.5	47.8
$RD_{AO,t}$	20.6	11.3	12.2	18.4	4.5	13.0	7.4	39.9**	87.4
B. Second Cholesky Order, Weakest to Strongest Inter-industry Links									
$RD_{28,t}$	49.2***	8.2	6.1	5.0	5.8	6.6	4.0	5.7	41.4
$RD_{33,t}$	4.3	30.2**	5.5	16.9	13.5	14.1	3.9	12.0	70.2
$RD_{34,t}$	6.1	16.3	45.2***	21.6	7.3	6.1	7.7	3.6	68.7
$RD_{35,t}$	2.3	7.1	9.0**	10.4*	7.2	2.4	3.3	1.8	33.1
$RD_{36,t}$	2.0	10.2	12.1*	16.7	47.3**	2.6	2.8	4.0	50.4
$RD_{37,t}$	5.5	2.1	2.8	3.4	9.6	44.3**	19.5	6.3	49.2
$RD_{38,t}$	5.0	13.6	10.2	12.7	5.4	11.1	49.0**	5.6	63.6
$RD_{AO,t}$	25.6	12.4	9.2	13.3	3.8	12.9	9.9	61.0**	87.1

This table displays the results of long-run variance decompositions of the model in table 3. Row *i*, column *j* is the proportion of industry *j*'s variance explained by industry *i*. The last column is the sum of off-diagonal elements. All entries are in percentages. This table describes Aircraft and Missiles (SIC 372, 376) as SIC 37 for simplicity of notation and the All Other industry as AO. Significant at ***1%, **5%, and *10%.

industries, and so on for the rest of the industries. Focusing on the disaggregated industries, relatively more interconnected industries tend to explain a larger portion of the variance of other industries. For example, industry 33 (the most interconnected industry) explains an average of $78.4\%/7 = 11.2\%$ of the variance of other industries. In contrast, industry 28 (the least interconnected industry) explains only an average of $34.4\%/7 \approx 4.9\%$ of the variance of other industries. Alternatively stated, the most interconnected industry explains *more than 220%* as much variance as the least interconnected industry.

Panel B in table 5 summarizes the variance decomposition results using the second Cholesky order. The second order should bias the results against finding an association between inter-industry links and R&D spending, as shocks to industries with weaker inter-industry links can contemporaneously affect the R&D of other industries but shocks to industries with stronger inter-industry links can affect other industries only with a lag. Again focusing on the disaggregated industries, as expected the second identification order reduces the impact of the more connected industries, but the results are largely consistent between the two identification schemes. For example, even with the identification order biased against industries with stronger links, the most interconnected industry still explains *more than 160%* as much variance as the least interconnected industry.

Table 6 further analyzes the variance decompositions. Reemphasizing the rationale behind looking at the variance decompositions: if the R&D of an industry is partly determined by the R&D of its suppliers or demanders, then the R&D of its suppliers or demanders should be useful in explaining the variance of the industry's R&D. To investigate this potential relationship, I consider the variance forecasts between pairs of industries. An industry pair consists of two industries, say, industries 28 and 33. The explained variance

TABLE 6.—VARIANCE DECOMPOSITION SUMMARY

	Cholesky Order	
	First Order	Second Order
Total inter-industry explained variance from the seven strongest supplier-demander pairs	175.5	162.9
Total inter-industry explained variance from the seven intermediate supplier-demander pairs	87.6	92.2
Total inter-industry explained variance from the seven weakest supplier-demander pairs	74.6	82.2
Total inter-industry explained variance	337.7	337.3
Ratio of explained variances: strongest set to weakest set	2.35	1.98

This table displays summary statistics from the variance decompositions in table 5 for the two- and three-digit SIC industries. The first Cholesky order is industries from strongest to weakest inter-industry links and corresponds to the variance decomposition in panel A of table 5. The second Cholesky order is industries from weakest to strongest inter-industry links in panel B of table 5. All entries except the ratio in the last row are in percents.

of this industry pair is the variance of industry 33 explained by industry 28, plus the variance of industry 28 explained by industry 33. More generally, for two industries *i* and *j*, the total explained variance of the industry pair is row *i*, column *j* plus row *j*, column *i* in table 5. Because there are 21 inter-industry pairings excluding the All Other industry, I split the sample evenly into three sets of seven inter-industry pairings. I compare the explained variance by the set of industry pairs with the stronger supplier-demander relationships to the explained variance by the sets of pairs with weaker supplier-demander relationships.

In table 6, the entries under First Order correspond to the variance decomposition in table 5, panel A and Second Order for panel B. The first row is the total inter-industry explained variance for the third of industry pairs with the strongest supplier-demander relationships, and so on for the sets of industry pairs with weaker supplier-demander relationships in the second and third rows. The fourth row is the total inter-industry explained variance.

The takeaway from table 6 is the last row: the ratio of the inter-industry explained variance coming from industries with a strong supplier-demander relationship versus those with a weak supplier-demander relationship. For the first Cholesky order, the average explained variance between an industry pair with a strong supplier-demander relationship is *over 230%* as much as between an industry pair with a weak supplier-demander relationship. Furthermore, when identifying shocks with the second Cholesky order (which should bias the results against finding a relationship between inter-industry links and R&D fluctuations), the average forecastable variance between industries with a strong supplier-demander relationship is still *over 190%* as much as between industries with a weak supplier-demander relationship.

Summarizing the results of the variance decompositions: for both identification schemes, the results show that the forecastable variance between industries with a strong supplier-demander relationship is higher than that between industries with a weak supplier-demander relationship. This evidence supports the results of the Granger causality tests, which suggest that the R&D of an industry changes in response to the R&D of an industry's suppliers and demanders.

V. Conclusion

This paper investigates a possible determinant of company-financed R&D spending. The hypothesis is R&D by an industry is influenced by the R&D of its suppliers and/or demanders. I construct measures of the supplier-demander relationship between industries with input-output tables consistent with Shea (1991). Using evidence from Granger causality tests supported by variance decompositions, the results imply a strong supplier-demander relationship between industries is associated with increased interconnectedness of their R&D. The findings are robust to controlling for the U.S. R&D tax credit, business cycles, and government-financed R&D.

If inter-industry linkages drive inter-industry R&D fluctuations, then there are some important implications for policy and associated research, for example, public subsidies for R&D-intensive firms. In general, a subsidy to a firm may change its R&D level and it may also change the R&D levels of any number of non-subsidized firms. The evidence from this paper suggests a change in the R&D level of a subsidized firm could lead firms linked to the subsidized firm by supplier-demander relationships to also change their R&D levels. Therefore, public money may be either stimulating or crowding out R&D across industries, so care must be used in the disbursal of subsidies.

In terms of economic research on the effects of public subsidies, inter-industry R&D comovement makes identification of a subsidy's effect on the subsidized firms problematic. The identification issue is particularly true of research that identifies the subsidy's effect based off of comparing subsidized firms to a group of non-subsidized firms. The presence of R&D spillovers, which includes the inter-industry fluctuations of R&D analyzed in this paper, between subsidized and non-subsidized firms invalidates using the non-subsidized firms as a control group (Klette, Møen, and Griliches, 2000). This research has not examined if changes in private R&D from a public subsidy exhibit the same type of comovement pattern as total private R&D. However, the potential for spillovers caused by subsidies between firms linked by supplier-demander relationships is a possibility and remains an open question.

While the results lend themselves to support the hypothesis that R&D has a strategic component, some care must be exercised in their interpretation. Of note is the results hold for industries where R&D data are available at the disaggregated two- or three-digit SIC level. Because the NSF censors data that will reveal the R&D of any single firm, the results give the strongest implication for industries where the industry's R&D is spread over a large number of firms. Fortunately, from the standpoint of understanding innovation, the industries available at the disaggregated two- or three-digit SIC level are particularly relevant to analyze because they compose the bulk of company-financed manufacturing R&D: an average of 74% (NSF, 2009). The disaggregated industries also encompass all of the high-tech manufacturing sector (Brown, Fazzari, & Petersen, 2009). A researcher could hypothesize about how an industry with a high R&D concentration among a few firms would make strategic R&D decisions, although this hypothesis is untestable with the available data.

REFERENCES

Arrow, Kenneth J., "Economic Welfare and the Allocation of Resources for Invention" (pp. 609–626), in Richard R. Nelson (ed.), *The Rate and Direction of Inventive Activity: Economic and Social Factors* (Princeton, NJ: Princeton University Press, 1962).

Barlevy, Gadi, "On the Cyclicality of Research and Development," *American Economic Review* 97:4 (2007), 1131–1164.

Becker, Wolfgang, and Jürgen Dietz, "R&D Cooperation and Innovation Activities of Firms—Evidence for the German Manufacturing Industry," *Research Policy* 33:2 (2004), 209–223.

Bloom, Nick, Rachel Griffith, and John Van Reenen, "Do R&D Tax Credits Work? Evidence from a Panel of Countries 1979–1997," *Journal of Public Economics* 85:1 (2002), 1–31.

Brown, James R., Steven M. Fazzari, and Bruce C. Petersen, "Financing Innovation and Growth: Cash Flow, External Equity, and the 1990s R&D Boom," *Journal of Finance* 64:1 (2009), 151–185.

Bureau of Economic Analysis (BEA), *BEA: Gross-Domestic-Product-by-Industry Accounts* (March 2011), http://www.bea.gov/industry/gpotables/gpo_action.cfm.

Cohen, Wesley M., and Daniel A. Levinthal, "Innovation and Learning: The Two Faces of R&D," *Economic Journal* 99:397 (1989), 569–596.

Goolsbee, Austan, "Does Government R&D Policy Mainly Benefit Scientists and Engineers?" *American Economic Review* 88:2 (1998), 298–302.

Granger, C.W.J., "Investigating Causal Relations by Econometric Models and Cross-Spectral Methods," *Econometrica* 37:3 (1969), 424–438.

Hall, Bronwyn H., and Nathan Rosenberg (eds.), *Handbook of the Economics of Innovation* (Amsterdam: North-Holland, 2010).

Harhoff, Dietmar, "Strategic Spillovers and Incentives for Research and Development," *Management Science* 42:6 (1996), 907–925.

Himmelberg, Charles P., and Bruce C. Petersen, "R&D and Internal Finance: A Panel Study of Small Firms in High-Tech Industries," this REVIEW 76:1 (1994), 38–51.

Klette, Tor Jakob, Jarle Møen, and Zvi Griliches, "Do Subsidies to Commercial R&D Reduce Market Failures? Microeconometric Evaluation Studies," *Research Policy* 29:4–5 (2000), 471–495.

Lach, Saul, "Do R&D Subsidies Stimulate or Displace Private R&D? Evidence from Israel," *Journal of Industrial Economics* 50:4 (2002), 369–390.

Lawson, Ann M., "Benchmark Input-Output Accounts for the U.S. Economy, 1992," *Survey of Current Business* 77:11 (1997), 36–82.

Lerner, Josh, "An Empirical Exploration of a Technology Race," *RAND Journal of Economics* 28:2 (1997), 228–247.

Liker, Jeffrey K., *The Toyota Way: 14 Management Principles from the World's Greatest Manufacturer* (New York City: McGraw-Hill, 2004).

National Science Foundation (NSF). *NSF's Research and Development in Industry (R&D in Industry) Historical Data* (August, 2009), http://www.nsf.gov/statistics/iris/.

——— *Research and Development in Industry: 2005. Detailed Statistical Tables NSF 10-319* (September 2010), http://www.nsf.gov/statistics/nsf10319/.

Norris, Guy, Geoffrey Thomas, Mark Wagner, and Christine Forbes Smith, *Boeing 787 Dreamliner: Flying Redefined* (Perth: Aerospace Technical Publications, 2005).

Ouyang, Min, "On the Cyclicality of R&D," this REVIEW 93:2 (2011), 542–553.

Powell, Walter W., and Stine Grodal, "Networks of Innovators" (pp. 56–85), in Jan Fagerberg, David C. Mowery, and Richard R. Nelson (eds.), *The Oxford Handbook of Innovation* (New York: Oxford University Press, 2006).

Samuelson, Paul A., "The Pure Theory of Public Expenditure," this REVIEW 36:4 (1954), 387–389.

Shea, John, "The Input-Output Approach to Demand-Shift Instrumental Variable Selection: Technical Appendix," University of Wisconsin Social Science Research Institute working paper 9115 (1991).

Solow, Robert M., "Technical Change and the Aggregate Production Function," this REVIEW 39:3 (1957), 312–320.

Wälde, Klaus, and Ulrich Woitek, "R&D Expenditure in G7 Countries and the Implications for Endogenous Fluctuations and Growth," *Economics Letters* 82:1 (2004), 91–97.

Wallsten, Scott J., "The Effects of Government-Industry R&D Programs on Private R&D: The Case of the Small Business Innovation Research Program," *RAND Journal of Economics* 31:1 (2000), 82–100.

Wilson, Daniel J., "Beggar Thy Neighbor? The In-State, Out-of-State, and Aggregate Effects of R&D Tax Credits," this REVIEW 91:2 (2009), 431–436.

Zellner, Arnold, "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias," *Journal of the American Statistical Association* 57:298 (1962), 348–368.