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DETERMINANTS OF RESEARCH AND DEVELOPMENT INTENSITY FROM A NETWORK PERSPECTIVE

TENG Joe K.L.
Sorrell College of Business, Troy University

HU Jiayu
Department of Computer Science, Troy University

WU Dazhong
Sorrell College of Business, Troy University

MIXON Phillip A.
Sorrell College of Business, Troy University

DUAN Chaojie (CJ)
Sorrell College of Business, Troy University

Abstract:

We model and examine the research and development (R&D) intensity of a focal industry from an inter-industry network perspective. More specifically, we estimate how a focal industry's R&D investment is affected by partner (suppliers and customers) industries' R&D expenditure. We also investigate the impact of the overall economy on the focal industry's R&D expenditure and finally how a focal industry's position in the supply chain network moderates the overall economy's impact on the focal industry's R&D expenditure. We found that, in general, a focal industry's R&D intensity is positively associated with its partner industries' R&D intensity. In addition, an industry's R&D intensity is positively associated with the growth rate of the overall economy. Finally, we found that a more central industry is subjected to a stronger impact of macroeconomic shocks on its R&D intensity though there is no significant association between an industry's centrality and its R&D intensity.

Key words: *R&D, R&D intensity, network model, centrality*

1. Introduction

Over the past few decades, research and development (R&D) intensity studies have been of great interest to scholars, policy makers and businesses. There are a burgeoning body of empirical studies in the value of R&D intensity, which examined the relationship between R&D investment and various measures of performance (Falk, 2012; Ghosh, 2012; Nunes, Serrasqueiro, & Leitao, 2013). Some studies also examine the impact of alliance portfolio complexity on innovative performance of companies (Duysters & Lokshin, 2011).

Currently, there is an emerging trend of literatures that empirically look at firm/industry innovation from the network perspective (Phelps, Heidl, & Wadhwa, 2012). Ahuja (2000) suggests that both the number of direct ties and indirect ties a firm maintains, positively affect its innovation output and an increase in structure holes is also associated with a decrease in innovation output. Melissa A. Schilling and Phelps (2007) suggest that firms with higher clustering coefficient and higher reach have higher innovation output. Furthermore, Melissa A Schilling (2015) indicates that technology shock, a firm's alliance activities, and a firm's network reach (an outcome of the size and density of the connected component within which a firm is embedded, and the firm's location within that component) each have significant and positive relationships with subsequent patenting output.

These existing literatures on network and innovation focus on alliance network. However, using alliance network approach may result in selection biases as firms select their alliance partners partly based on the matches between their R&D expenditures. Therefore, the formation of alliance network is not exogenous when we compare R&D intensities among alliance network partners. On the other hand, industrial trading networks are not subjected to the aforementioned bias. For example, that the auto industry needs to buy from the tire industry is based on the production requirements and can be considered exogenous when we study the two industries' R&D expenditures. This study offers a novel empirical approach by analyzing the relationship of a focal industry's innovation and network characteristics from the perspective of a trading network.

This paper intends to increase the body of research using a statistical/econometric approach. We organize this paper as follows. We first present the research methodology. We then describe the data and variables, followed by model description and the empirical analysis. We finally summarize the paper and provide recommendations for future studies.

2. Methodology

In this study, we have three research questions: (1) In supply chain network, what is the impact of partner (suppliers and customers) industries' R&D investment on the focal industry's R&D expenditure? (2) What is the impact of the overall economy on the focal industry's R&D expenditure? and (3) How does a focal industry's position in the supply chain network moderates the overall economy's impact on the focal industry's R&D expenditure? To answer these questions, we need to first construct the Inter-Industry supply chain network.

Construction of the Inter-Industry Network

The Inter-Industry Network used in this study is constructed from the annual USE table released by the US Bureau of Economic Analysis (BEA). The USE table provides information on products used by 66 non-government industries in the United States. For each year from 1998 to 2011 an inter industry network was constructed. The nodes in the constructed network represent the industry and the links connecting these nodes represents the trading relationships between the industries. The weights of these links are based on trading relationship between the two industries. More specifically, for any two industries *i* and *j* ($j \neq i$), let U_{ij} (U_{ji}) be the amount of industry *i*'s (*j*'s) products, in terms of dollar value, used by industry *j* (*i*) as inputs. Using the approach by Aoibda, Caskey, and Ozel (2014) the weight of the link between industries *i* and *j* was calculated as:

$$A_{ij} = \frac{1}{4}\left(\frac{U_{ij}}{\sum_k U_{ik}} + \frac{U_{ij}}{\sum_k U_{kj}} + \frac{U_{ji}}{\sum_k U_{jk}} + \frac{U_{ji}}{\sum_k U_{ki}}\right) \qquad (1)$$

In equation (1) above the four ratio, $U_{ij}/\sum_k U_{ik}$, $U_{ij}/\sum_k U_{kj}$, $U_{ji}/\sum_k U_{jk}$, and $U_{ji}/\sum_k U_{ki}$ are the proportion of industry *i*'s products sold to industry *j*, the proportion of industry *j*'s purchased products produced by industry *i*, the proportion of industry *j*'s products sold to industry *i*, and the proportion of industry *i*'s purchased products produced by industry *j* respectively. Therefore, the four ratios measure how important one industry is as a supplier or customer to the other industry from their perspectives. The four ratios are calculated for each pair of industries, *i* and *j*, and the average is taken to measure how heavily industry *i* and industry *j* rely on the trade flow between each other. The adjacent matrix A, based on A_{ij} as defined in Equation (1):

$$A = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1m} \\ A_{21} & A_{22} & \cdots & A_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ A_{m1} & A_{m2} & \cdots & A_{mm} \end{bmatrix} \qquad (2)$$

In the matrix above, m is the number of industries. Note that the matrix is symmetric and for each year an adjacent matrix was created to reflect the inter-industry flows of products in the year. Also, following the literature the diagonal elements (e.g., A_{11} and A_{mm}) in each adjacent matrix are set to zero. Figure 1 shows the inter-industry network for year 2005:

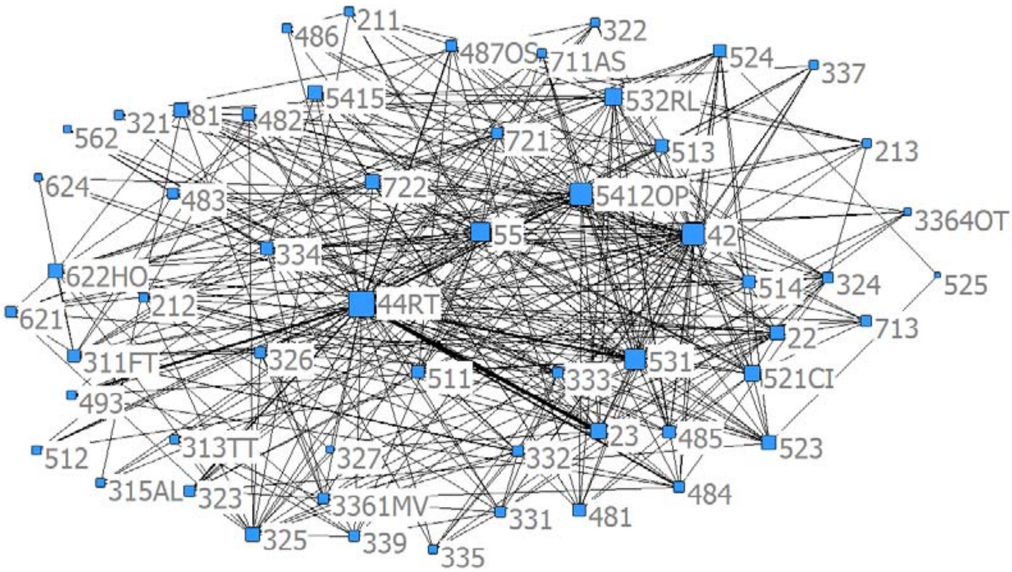

Figure 1: Inter-Industry Network Based On BEA Input-Output Table 2005 (filtered for illustration purposes)

In Figure 1, each node represents an industry. If industry *i* sells its products to industry *j*, then a link is formed between these two corresponding nodes, and the weight of the link, A_{ij} (defined in Equation (1)), is represented by its width. For example, the thicker link connecting Retail Trade (ID 44RT), and Construction (ID 23) represents a stronger trading relationship between the two industries than a narrower link in the network. The entire inter-industry network in year 2005 consists of 56 nodes and 1485 links. For illustration, a filter was applied to exclude weights less than 0.02, resulting in a network with 56 nodes and 356 links (Figure 1). However, the entire network with all nodes and links were used for the analysis.

Dependent Variable

The dependent variable in this study is R&D intensity which is defined as R&D expenditure divided by sales (Wesley M. Cohen & Klepper, 1992). We collected data on industrial R&D expenditure between 1998 and 2011 from US BEA. The industries included in the R&D dataset by BEA directly correspond to industries in the input-output table at the summary level, though BEA only reports R&D expenditure for 56 industries. Merging the two datasets results in a panel data with 56 industries for14 years. Please refer to **Error! Reference source not found.** for industries included in the model.

Independent Variables

The independent variables in this study include partner R&D intensity, centrality, macro-economic shocks, and industry size.

Partner R&D Intensity

For a focal industry *i* in year *t*, its partner R&D intensity Z_{it} is the weighted average of its partner industries' R&D intensity (i.e., industries that are directly connected to industry *i* in the inter-industry network). Hence, the partner R&D intensity of industry *i* in year *t* is

$$Z_{it} = \sum_{j \neq i} \frac{A_{ij}}{A_{i*}} Y_{jt} \quad (3)$$

where A_{ij} is defined in Equation (1), $A_{i*} = \sum_k A_{ik}$, and Y_{jt} is the R&D intensity of industry *j* in year *t.* For example, suppose industry *i* has two partner industries. Let the two industries be A and B. Suppose in the inter-industry network the weights of the trading links from industry *i* to A and to B are 0.8 and 0.2 respectively, and R&D intensities of industries A and B are Y_A and Y_B respectively, then industry *i*'s partner R&D intensity is $\frac{0.8}{0.8+0.20} \times Y_A + \frac{0.2}{0.8+0.2} \times Y_B = 0.8 \times Y_A + 0.2 \times Y_B$.

Centrality

In this study an industry's position in the network is measured using its eigenvector centrality in the network. Following the approach of Aoibda et al. (2014) and Newman (2003), we first calculate the principle eigenvector C of the adjacency matrix A (defined in Equation (2)) that satisfies:

$$AC = \lambda C$$

In the inter-industry network, the eigenvector centrality of the *i* *th.* node is the *i* *th.* item of vector *C*, denoted by C_i. Hence:

$$C_i = \frac{1}{\lambda} \sum_{j \neq i}^{m} A_{ij} C_j$$

As illustrated earlier, each industry in Figure 1 is shown as a node. In the figure, we use the size of the node to represent the level of eigenvector centrality of the corresponding industry. For example, industries such as Retail Trade (ID 44RT) and Miscellaneous Professional, Scientific, and Technical Services (ID 5412OP) have more connections to other industries, and therefore are among the most central industries. On the other hand, examples of the least central industries include Funds, Trusts, and Other Financial Vehicles (ID 525) and Other Transportation Equipment (ID 3364OT).

Macro-economic Shocks

GDP data between 1997 and 2011 was collected from BEA. The macro-economic growth for year *t* is $\log(GDP_t / GDP_{t-1})$. This variable is included for two reasons. First, this variable may affect each industry's R&D intensity. In other words, each industry may adjust its R&D intensity based on the growth rate of the whole economy. Since this variable influences both the dependent variable and partner R&D intensity, excluding this variable from the model will result in biased estimates. Second, this study is interested in whether central industries and non-central industries react differently to macroeconomic shocks such as GDP growth when they determine their R&D expenditures.

We also include the natural logarithm of each industry's number of employees to control for size. After calculation, the final dataset is a balanced panel dataset covering 14 years with 56 industries at the 3-digit NAICS level.

The independent and dependent variables used in the models are summarized in Table **1**. The correlations of the variables are shown in Table 2.

Table 1: Variables and Sample Summary Statistics

	Mean	Std. Deviation	Min	Max
Industry RD intensity	0.014	0.026	0.000	0.203
Partner RD intensity	0.014	0.008	0.001	0.056
Centrality	0.016	0.016	0.002	0.112
Macroeconomic Shocks	0.020	0.019	-0.028	0.046
Size	6.742	1.241	3.638	9.665
Observations	**784**			

Table 2: Correlation Table

	Y	Z	C	S	Emp
Industry RD intensity (Y)	1				
Partner RD intensity (Z)	0.1685*	1			
Centrality (C)	-0.0783*	-0.2416*	1		
Macroeconomic Shocks (S)	-0.0303	-0.0831*	-0.0001	1	
Size (Emp)	-0.0075	0.0179	0.3211*	0.0167	1

* p<0.10

3. Model and Discussion

The Model

In the regression analysis, the following panel data dynamic model was used on the balanced dataset with 56 industries over 14 years from 1998 to 2011:

$$Y_{it} = \beta_0 Y_{i,t-1} + \beta_1 Z_{i,t-1} + \beta_2 S_t + \beta_3 (S_t \cdot C_{it}) + \beta_4 C_{it} + \beta_5 Emp_{i,t-1} + F_i + \sum_{j=1}^{13} \rho_j \tau_j + \varepsilon_{it} \quad (4)$$

In the equation, Y_{it} is the natural logarithm of industry *i*'s R&D intensity in year t. $Y_{i,t-1}$ is the natural logarithm of industry *i*'s R&D intensity in year $t-1$. Including the lagged dependent variable $Y_{i,t-1}$ allows this model to account for the persistence in industry R&D intensity. Therefore, the model looks at how a focal industry's R&D intensity is influenced by its partner industries' R&D intensities, its position in the industry network, and macro-economic shocks, while controlling for the focal industry's within-industry time-series variation. On the other hand, including the lagged dependent variable $Y_{i,t-1}$ introduces endogeneity. Therefore, we adopted the approach proposed by Arellano and Bond (1991) and Blundell and Bond (1998) to estimate the dynamic model.

$Z_{i,t-1}$ represents the natural logarithm of industry *i*'s partner industries' R&D intensity in year $t-1$. S_t represents the macro-economic shocks that each industry receives in year t. We include S_t partly because it is related to our research questions, and partly because we need to control for macro-economic shocks; otherwise the results could be ambiguous when we examine the impact of partner industries' R&D intensities on a focal industry's R&D expenditure. For example, with S_t excluded, a positive β_1 could mean a positive association between focal industry and its partner industries' R&D intensities, or could mean a co-movement of these expenditure variables: industries are exposed to macroeconomic shocks, and therefore as industries decide their R&D intensities given the same macroeconomic shocks their R&D intensities move in the same direction (increase or decrease).

C_{it} is industry *i*'s centrality in year *t*. In the model, we include the interaction term, $S_t \times C_{it}$ to examine whether more central industries react differently to macro-economic shocks compared with non-central industries. $Emp_{i,t-1}$ is industry *i's* size in year $t-1$. F_i represents the time-invariant individual fixed effects for industry *i*. r_j ($j = 1, \dots, 13$) is the dummy variable for year *j* to capture the year fixed effects. Finally, ε_{it} is the error term.

In our regression, we performed common diagnostic tests for dynamic panel models (Cameron & Trivedi, 2010) to ensure our model is well specified. First, we ran the Arellano-Bond test for autocorrelation, and the test failed to reject the null hypothesis of no serial correlation in first-differenced errors at order two or higher. This justifies the selection of the model. Second, we performed the Sargan-Hansen test of over-identification restrictions. The test failed to reject the null hypothesis that the instrument variables are exogenous. Third, by default the estimation process will choose as many lags (starting from the second lag) of dependent variables as possible to be instruments. As our dataset covers a long period of 14 years and as a result the default regression process may introduce too many instruments with a possible loss of efficiency. Therefore, in our regression we only used the second and the third lags of the dependent variable as GMM instruments to follow the rule of thumb that the number of instrument variables is less than the number of panels.

Discussion

The regression results are shown in
Table **3**.

Table 3: Regression Results

Independent Variables	Estimates
Lagged industry RD intensity	0.897***
	(0.046)
Partner RD intensity (β_1)	0.122*
	(0.055)
GDP growth (β_2)	5.649**
	(1.949)
GDP growth x Centrality (β_3)	35.962*
	(16.882)
Centrality (β_4)	-3.540
	(2.336)
Size (β_5)	-0.006
	(0.016)
Observations	728[1]

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Robust standard errors are shown in parentheses. Coefficients for the year dummy variables are omitted.

Impact of Partner R&D intensity

From

Table **3**, β_1 is positive and significant (P value = 0.027), this indicates that a focal industry's R&D intensity is positively associated with its partner industries' R&D intensity. This suggest that the likelihood that a focal industry increases (decreases) its R&D intensity is greater if there is an increase (decrease) in R&D intensity among the industries that the focal industry is directly connected to. The lagged partner R&D intensity ($Z_{i,t-1}$) used in the model indicates the possibility that the increase (decrease) in R&D intensity flows through the industry network and affects each industry in the network.

This finding is consistent with the literature on R&D cooperation in supply chain management. The vertical cooperation in R&D between suppliers and customers allows knowledge to flow through the supply chain network and add values to supply chain members, as external source of complementary knowledge transferred from suppliers or customers increases members' competitive advantage (Frels, Shervani, & Srivastava, 2003). For example, by forming R&D alliance with its suppliers, a focal firm is able to reduce its production costs and improve its product quality (Das, Narasimhan, & Talluri, 2006). On the other hand, vertical cooperation in product innovation with customers enables a focal firm to gain better understanding of the market trends and as a result design/develop its new products more quickly to capture new market opportunities (Corsten & Kumar, 2005).

The literature also indicates that, conditional on their own expenditures on R&D, different firms may get different levels of technology spillovers from their

[1] There are 728 (=56×13) observations rather than 784 (=56×14) observations as in
Table **1**, due to the use of lagged explanatory variables in the regression; data in 1997 are used to calculate lagged variables for the regression in 1998.

suppliers and customers. This is because a firm's capabilities to learn from the pool of knowledge transferred from its supply chain partners are influenced by its investments in technology innovations (Fung, 2005). As a result, given the interdependence of R&D activities among supply chain members, a firm may adjust its R&D intensity based on the changes of R&D intensities of its suppliers and customers.

Impact of Macro-Economic Shocks

In this model, the overall impact of macro-economic shocks (S_t) on the focal industry's R&D intensity is

$$\frac{\partial y_{it}}{\partial S_t} = \beta_2 + \beta_3 C_{it} \qquad (5)$$

In our regression, we centered both S_t and C_{it} following the steps suggested by Aiken and West (1991). Therefore, β_2 reflects the impact of macro-economic shocks (S_t) on the focal industry's R&D intensity (y_{it}) when the focal industry's centrality (C_{it}) is at its mean (zero). On the other hand, β_3 measures the moderating role of centrality on the impact of macro-economic shocks on focal industry's R&D intensity. As shown in

Table **3**, both β_2 and β_3 are positive and significant (P values are 0.004 and 0.033 respectively). Given this, $\partial y_{it}/\partial S_t$ takes its lowest value (5.14) when the centered C_{it} is at its minimum (−0.014), and increases as C_{it} increases. Therefore, we always have $\partial y_{it}/\partial S_t > 0$ which indicates that an industry's R&D intensity is positively associated with the growth rate of the overall economy. In other words, when the overall economy is growing faster, industries tend to raise their R&D intensities, and when the economy slows down industries reduce their R&D intensities.

On the other hand, when centrality increases, $\partial y_{it}/\partial S_t$ increases and becomes stronger. This indicates that a more central industry is subject to a stronger impact of macroeconomic shocks on its R&D intensity. To put it in another way, when the economy is booming (or slowing down), a more central industry increases (or decreases) its R&D intensity more than a less central industry does. This is because an industry's centrality is associated with its exposure to the economy. A more central industry has more connections to other industries, and this enables it to sense the movement of an economy upturn or downturn earlier and thus adjust its R&D faster than a non-central industry.

In this model, the overall impact of centrality (C_{it}) on R&D intensity is

$$\frac{\partial y_{it}}{\partial C_{it}} = \beta_4 + \beta_3 S_t$$

In our model, β_4 measures the impact of centrality on R&D intensity when S_t is at its mean (zero) (corresponding to a growth rate of 2% as shown in

Table **1**) as we centered both S_t and C_{it}. β_4 is not significant. On the other hand, β_3 is positive and significant. To study the overall impact of centrality on R&D intensity, we let S_t change from its lower limit to its upper limit, and calculate the corresponding $\partial y_{it}/\partial C_{it}$ and its standard error. For the whole range of S_t, $\partial y_{it}/\partial C_{it}$ is not significant at the 5% level. In other words, there is no significant statistical association between an industry's centrality and its R&D intensity. One explanation is that the impact of a focal industry's position in the network is driven by different forces in the opposite directions and as a result the outcome is not determined. A more central industry is more connected and therefore closer to other industries, which may lead to a stronger impact of partner industries' R&D intensities. On the other hand, a more central industry is also connected to a variety of partner industries and their diversity (e.g., some may increase R&D intensity while others decrease) may reduce the impact of their R&D intensity as impacts from different partner industries may to a certain extent cancel out each other.

4. Conclusions and Recommendations for Future Research

This paper examines industries' R&D intensities from an inter-industry network perspective. Our focus in the paper is on how such a network environment affects a focal industry's R&D expenditure.

We found that a focal industry's R&D intensity is in general positively associated with its partner industries' R&D intensity. In other words, R&D capital stock of its partners could influence a focal industry's R&D investment decisions. More specifically, increased R&D intensity from suppliers/customers may motivate a focal industry to increase its R&D expenditure in pursuit of enhanced R&D cooperation, and better absorption of complementary knowledge provided by partners, as previous research has shown that industries with more internal R&D activities are characterized by higher capabilities to absorb external knowledge (Badillo, Llorente, & Moreno, 2014; Wesley M Cohen & Levinthal, 1990).

Our results also indicate that an industry's R&D intensity is positively associated with the growth rate of the overall economy. Industry companies tend to raise their R&D intensities when the overall economy is growing fast. In addition, we found that a more central industry is subject to a stronger impact of macroeconomic shocks on its R&D intensity. In other words, a more central industry tends to be more exposed and influenced by external economic environment than a less central industry does. An economic movement will have a greater impact on a focal industry's R&D intensity if it has more connections with partners.

Our study contributes to the R&D literature by explicitly modeling the industries as a network of suppliers and customers. We believe that this network approach extends our research on determinants of R&D intensity from a new perspective.

In this paper, all of our calculations are based on industry-level rather than firm-level data. We use industry-level data mainly because detailed firm-level information is not available from public websites. Future research could benefit from richer datasets, which provide more detailed information for each focal firm rather than industry.

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