Pro-cyclical Aggregate R&D: A Comovement Phenomenon

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March 2011

Abstract

Pro-cyclical aggregate R&D has been taken as evidence against the conventional Schumpeterian view on the optimal timing of innovation. We decompose aggregate R&D and real GDP in the U.S. into those by 22 industry groups. Surprisingly, we find only 5.67% of pro-cyclical aggregate R&D reflects within-industry timing of innovation and production, but 94.37% arises from inter-industry co-movement between R&D and output. We posit pro-cyclical aggregate R&D, just like the business cycle itself, is a comovement phenomenon.

* Email: mouyang@uci.edu. Hugo Hopenhayn, Tony Braun, and Seminar participants at USC, the Brookings Institution, 2010 Midwest Macro Meeting, 2010 LACEA, the Atlanta Fed, and UC-Irvine provided helpful discussions. All errors are mine.

1. Introduction

The literature has repeatedly documented aggregate R&D is pro-cyclical. For example, Fatas (2000), Walde and Woitek (2004), Comin and Gertler (2006), and Barlevy (2007) show growth in aggregate R&D expenditures tracks GDP growth for the U.S. , for G7 countries, over the business-cycle frequency, and over the medium-term frequency. However, the optimal timing of productivity-improving activities, including R&D, should be counter-cyclical, according to the conventional Schumpeterian view arguing the opportunity cost of such activities as forgone output is lower during recessions.[1] Hence, pro-cyclical aggregate R&D has been taken as evidence against the Schumpeterian view, and has motivated many authors to devise models proposing factors distorting the optimal timing of innovation (Aghion et al., 2005; Barlevy, 2007; Francois and Lloyd-Ellis, 2009).

This paper aims to gain a better understanding of pro-cyclical aggregate R&D or, more specifically, to what extent such pro-cyclicality holds against the conventional Schumpeterian view. We are motivated by the fact that the business cycle itself is a co-movement phenomenon (Christiono and Fitzgerald, 1998): various sectors move up and down together over time, and such co-movement accounts for the majority of the observed aggregate fluctuations. This gives rise to the question whether pro-cyclicality of aggregate R&D – the fact that aggregate R&D moves *with* the business cycle – is also driven by comovement. If yes, then pro-cyclical aggregate R&D may arise from an aggregate bias instead of reflecting the timing of innovation.

To understand this point, consider a simple example. Suppose an economy is composed of two sectors only: Sector A and Sector B: A is the dominating production sector and B is the dominating R&D sector; each sector innovates more when producing less itself. Furthermore,

[1] This view traces back to Schumpeter (1939) and has been revived by authors such as Hall (1991), Aghion and Saint-Paul (1998), and Davis and Haltiwanger (1999).

suppose output by Sector A and that by Sector B display a negative correlation over time. In this example, aggregate R&D appears pro-cyclical, because B's R&D that dominates aggregate R&D happens to track A's output that dominates real GDP, not because A or B innovate more when producing more themselves. This example suggests aggregate R&D can track real GDP even if micro-level producers do choose the timing of their innovation according to the Schumpeterian view.

To explore this possibility, we decompose aggregate R&D and aggregate output into those at the industry level, and the covariance between aggregate R&D growth and real GDP growth into two components – a "within-industry" component reflecting how R&D and output co-vary within each industry on average, and a "cross-industry" component capturing how R&D and output co-move across industries. Applying such decomposition to the case of the U.S. from 1958 to 1998, we find the across-industry component at about the two-digit SIC level accounts for 94.37% of the covariance between aggregate R&D growth and real GDP growth. In other words, the observed pro-cyclical aggregate R&D is also a co-movement phenomenon just as the business cycle itself, at least in the case of the U.S.. We estimate such inter-industry R&D-output comovement amplifies by about five times the cyclicality of industry R&D at approximately the two-digit SIC level.

Based on our results, we argue the literature should be cautious when concluding the cyclicality of R&D is inconsistent with the Schumpeterian view only based on the aggregate data. According to our decomposition results, the "within-industry" component remains positive, implying industry R&D is still pro-cyclical on average; however, its magnitude declines sharply as the decomposition moves to more detailed industry levels. This points to the possibility the average pro-cyclicality of industry R&D is still driven by co-movement between R&D and output across heterogeneous producers. Moreover, the cyclicality of R&D differs significantly across our sample industries: R&D is counter-cyclical for some industry, but strongly pro-cyclical for some others. Based on these findings, we propose that industry-level or firm-level data should be employed to examine the timing of R&D and to explore when and why the Schumpeterian view fails the data.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 carries out the decomposition exercises. Section 4 concludes.

2. Data

Data on R&D by industry is taken from the National Science Foundation (NSF) that publishes nominal R&D expenditures for 21 manufacturing industry groups mostly at the level of approximately two-digit 1987 SIC from 1958 to 1998. The R&D-by-industry series are truncated by the year of 1998 because later series are published according to the North American Industry Classification System (NAICS), and the transformation between SIC and NAICS is not recommend by the NSF. [2] The NSF publishes both company-financed and federal-financed R&D. Only data on company-financed R&D are used, as our purpose is whether R&D's cyclicality contradicts the Schumpeterian view on entrepreneurs' optimal timing of innovation. Some industry-year observations are suppressed to avoid disclosure of individual firms' operations. However, in all but three of these observations, either company-financed R&D or total R&D is suppressed, but not both. Following Shea (1998), we use growth in total R&D to interpolate gaps in the series of company-financed R&D. The three observations where

[2] To make the year-to-year comparison more convenient, the NSF transforms the 1997-1998 R&D-by-industry series under the SIC into those under the NAICS. Unfortunately, the concordance behind the transformation remains confidential. Moreover, it is claimed that "the estimates for 1997 and 1998 (after transformation) are not necessarily representative of the NAICS categories of industries in those years…as it may involve a large number of errors." (http://www.nsf.gov/statistics/srs01410/).

company-financed R&D and total R&D are both suppressed are R&D by Textile and Apparel (SIC 22 and 23) in 1989, R&D by Rubber (SIC 30) in 1991, and R&D by Other Equipments (SIC 361-364, 369) in 1991. We interpolate these three gaps using growth in company-financed R&D based on the original NSF publications back in 1988, 1989, 1990, and 1991.[3] The NSF does not publish data on R&D by detailed non-manufacturing industries until 1995; rather, it provides series of total non-manufacturing R&D. This gives us a panel of R&D for 22 industry groups.

Data on output are from two resources. The manufacturing production data is from the NBER manufacturing productivity (MP) database that publishes data on production for 469 four-digit manufacturing industries from 1958 to 1996, and recently extended to 2005. Our results are robust to leaving the extended part of the data out of the analysis. Data on non-manufacturing output is from the series of GDP by industries published by the Bureau of Economic Analysis (BEA). It is important to note the NSF R&D data, the MP data, and the BEA GDP series are all compiled from surveys based on the same sample frame -- Standard Statistical Establishment List (SSEL) – maintained by the Census Bureau. This implies a good match of the three data sources. Since the MP data is provided at the most detailed 4-digit SIC level, we aggregate the MP production data according to the R&D industry definitions by the NSF, which, together with the R&D panel and the BEA non-manufacturing output series, gives us a panel of R&D and output by 22 industry groups from 1958 to 1998.

[3] These three observations, while suppressed in the revised series, were not missing in the original publications at http://www.nsf.gov/statistics/iris/excel-files/nsf_92-307/b-2.xls, http://www.nsf.gov/statistics/iris/excel-files/nsf_94-325/a-7.xls, http://www.nsf.gov/statistics/iris/excel-files/nsf_94-325/a-7.xls.

Output is measured as real value added, as the deflated value added using shipment-value-weighted price deflator.[4] Following Barlevy (2007) that examines aggregate R&D's cyclicality, we convert the R&D series into 2000 dollars using the GDP deflator. Table 1 lists the 22 industry groups in Column 1, their R&D shares in Column 2, and output shares in Column 3. Manufacturing industries are further grouped by those of non-durable goods and of durable goods. Table 1 shows R&D in the U.S. is overwhelmingly dominated by the manufacturing sector: it accounts for 92.19% of the observed total R&D expenditures, among which 25.65% is from non-durable manufacturing industries and 66.54% is from durable manufacturing industries. By contrast, only 20.52% of real GDP is from the manufacturing sector, among which non-durable manufacturing industries take 8.07% and durable manufacturing industries take 12.45%.

Two factors contribute to the dominance of manufacturing R&D on aggregate R&D in the U.S. reported by the NSF. First, the manufacturing sector is indeed an important innovating sector: it is a major provider of intermediate goods and capital goods for the rest of the U.S. economy; and intermediate-good producers are usually active innovators. Second, the NSF R&D series are compiled from the Industry Survey of Research and Development that was designed back in the 1950s when the U.S. economy was largely manufacturing based. Therefore, this survey is inevitably biased toward manufacturing firms and thus may have missed a significant amount of non-manufacturing R&D in reality.

[4] According to Bartelsman and Gray (1996), value added is adjusted for inventory changes while value of shipment is not. For our purpose of examining the correlation between R&D and production, value added is a more appropriate measure of output that includes both sold and unsold goods. Nonetheless, the results remain similar when output is measured as deflated value of shipments. Details are available upon request.

3. Decomposition

Following Shea (1996) and Comin and Philippon (2005), we approximate the growth rate of aggregate R&D, denoted as *R*, and that of aggregate output, denoted as *Y*, as the weighted averages of R&D growth and output growth by *N* disaggregated industries:

$$(1)\quad \begin{aligned} R_t &\cong \sum_{i=1}^{N} S_i^R R_{it} \\ Y_t &\cong \sum_{i=1}^{N} S_i^Y Y_{it} \end{aligned}$$

S_i^R and S_i^Y are industry *i*'s long-run shares of aggregate R&D and aggregate output. Let S^R and S^Y to be 1-by-*N* vectors whose elements are S_i^R and S_i^Y; let Ω^{RR}, Ω^{YY} and Ω^{RY} to be *N*-by-*N* variance-covariance matrixes of industry R&D, of industry output, and between industry R&D and industry output; let $Var(R_t)$ to denote the variance of aggregate R&D growth, $Var(Y_t)$ to be that of aggregate output growth, and $Cov(R_t, Y_t)$ to be the covariance between aggregate R&D growth and aggregate output growth. Then, $Var(R_t)$, $Var(Y_t)$, and $Cov(R_t, Y_t)$ are approximately:

$$(2)\quad \begin{aligned} Var(R_t) &\cong S^R \Omega^{RR} S^{R}{}'; \\ Var(Y_t) &\cong S^Y \Omega^{YY} S^{Y}{}'; \\ Cov(R_t, Y_t) &\cong S^R \Omega^{RY} S^{Y}{}'. \end{aligned}$$

(2) decomposes the variances of *R* and *Y* and their covariance into "within-industry" components and "cross-industry" components. For example, consider $Cov(R_t, Y_t) \cong S^R \Omega^{RY} S^Y$. Its "within-industry" component equals the share-weighted sum of the diagonal elements of Ω^{RY}, reflecting how R&D growth and output growth co-vary within industry on average. Its "cross-industry" component equals the share-weighted sum of the off diagonal elements of Ω^{RY},

capturing inter-industry co-movements between R&D growth and output growth. Similar interpretation holds fo $Var(R_t)$ and $Var(Y_t)$.

3.1 Decomposition Results

We apply (2) to our industry panel of R&D and output. The decomposition results are summarized in Table 2. Aggregate R&D and real GDP are decomposed into two groups in Panel A as manufacturing and non-manufacturing sectors, into three groups in Panel B as non-durable manufacturing industries, durable manufacturing industries, and non-manufacturing sectors, and into 22 groups in Panel C as 21 manufacturing industry groups and non-manufacturing sectors. The observed variances of aggregate R&D growth, real GDP growth, and their co-variance are reported in Column 1; the approximated values based on (2) are in Column 2; Column 3 and 4 divide the approximated values into "within-industry" components and "cross-industry" components. Column 5 lists the fractions of the approximated values attributable to the cross-industry components. Column 6 reports the averages of the pair-wise correlation coefficients between industry output growths, between industry R&D growths, or between industry R&D and output growths. In summary, Table 2 suggests the following.

Firs, not surprisingly output co-moves positively across industries. For example, according to Panel C, the pair-wise correlation coefficients of industry output growth average 0.4629; inter-industry output co-movement at approximately the two-digit SIC level accounts for 63.08% of volatilities in real GDP growth. This is consistent with the existing literature that documents the business cycle as a "co-movement" phenomenon. For example, Christiano and Fitzgerald (1998) show that most sectors are observed to move up and down together over the business cycle in the U.S.; Shea (1995) documents inter-industry employment co-movement at the three-digit SIC level accounts for about 95% of volatilities in total U.S. manufacturing employment; he also reports that quantitatively similar results hold for output.

Second, inter-industry R&D co-movement is not as strong as inter-industry output co-movement. The pair-wise correlation coefficients between industry R&D growths are negative both in Panel A and in Panel B, suggesting inter-industry R&D co-movement *dampens* rather than facilitates aggregate R&D volatilities. In Panel C, the average pair-wise correlation coefficient turns positive, but is very small quantitatively; inter-industry R&D co-movement at approximately two-digit SIC level accounts for 13.56% of aggregate R&D volatilities.

Third, R&D and output co-move positively with each other across industries. The average pair-wise correlation coefficients between industry R&D growth and industry output growth are positive in all three panels. Most importantly, such co-movement plays a dominant role in driving aggregate R&D pro-cyclical: its share of the approximated covariance between aggregate R&D growth and real GDP growth is 50.66% in Panel A, 91.16% in Panel B, and 94.37% in Panel C. In other words, inter-industry co-movement of R&D and output at approximately the two-digit SIC level accounts for 94.37% of the pro-cyclicality of aggregate R&D, but inter-industry co-movement of output takes only 63.08% of volatilities in real GDP. This suggests that inter-industry co-movement is a key factor in explaining the pro-cyclicality of aggregate R&D, even more so than its role in accounting for aggregate output volatilities that has long been recognized in the literature.

3.2 Cyclicality of R&D: aggregate v.s. disaggregate

Pro-cyclical aggregate R&D has been taken as evidence against the conventional Schumpeterian view. This view argues that, as long as innovation competes with production for resources, a rational entrepreneur who balances innovation and production inter-temporarily would choose to perform more R&D when the return to output, as the opportunity cost of R&D, is low.[5] Under the representative-firm paradigm, this view contradicts the observed pro-cyclicality of aggregate R&D. Now consider a framework of heterogeneous firms, and let our sample industries to represent firms that produce various products and engage in various innovation activities. Then (2) suggests that the average timing of R&D, as whether an industry's R&D is concentrated when its own output is low or when it is high, is reflected by the "within-industry" component. But our decomposition results suggest that it is the cross-industry component, as capturing how each industry's R&D co-moves on average with other industries' output that dominates the pro-cyclicality of aggregate R&D.

How would such inter-industry R&D-output comovement influence the estimated cyclicality of R&D? To address this question, we perform simple OLS estimations following Barlevy (2007) and Ouyang (2010), at the purpose of comparing the cyclicality of aggregate R&D with that of industry R&D.[6] In particular, we estimate the following two equations:[7]

$$\textbf{(3)}R_t^A = \alpha + \beta(L)Y_t^A + \varepsilon_t$$

$$\textbf{(4)}R_{it} = \alpha_i + \beta(L)Y_{it} + \gamma D_t + \varepsilon_{it}$$

In equation (3), R_t^A is the real aggregate R&D growth in year t; Y_t^A is the real GDP growth in year t. α is a constant. $\beta(L)$ is a lag polynomial with lag length L. Estimates on $\beta(L)$ in equation (3) capture the cyclicality of aggregate R&D. In equation (4), R_{it} is the real R&D growth of industry i in year t; Y_{it} is the output growth of industry i in year t. α_i is a set of industry dummies;

[5] Aghion and Saint-Paul (1998) propose that, if innovation requires produced goods instead of factors of inputs, the optimal timing of innovation should be pro-cyclical. However, Griliches (1990) argues that the major input into R&D is labor, not produced goods.

[6] Ouyang (2010) also perform instrumental-variable estimations on the cyclicality of industry R&D using aggregate data as instruments, which generates qualitatively similar results at the industry level.

[7] All estimations are conducted using growth rates (log-first differences). Panel unit-root test following Levin et al.(2002). All tests employ industry-specific intercepts and two lags. The results suggest the series of real R&D expenditure of real value added contain a unit root in log levels, but are stationary in log-first differences and are not co-integrated.

D_t is a set of year dummies. β(L) is a lag polynomial with lag length L, and estimates on β(L) in equation (4) reflect the *average* cyclicality of industry R&D, namely, how each industry balance their own production and innovation on average.

We apply the 1958-1998 data on real aggregate R&D and real GDP in the U.S. to estimate (3) and apply the 22-industry panel covering the same sample period to estimate (4). The OLS estimation results are summarized in Table 3. Only the results with L=0 and L=1 are reported. Our results are robust to longer lag lenths or to replacing year dummies with quadratic time trends as in Ouyang (2010). All additional results are available upon request.

Panel A of Table 3 presents the results on the estimated cyclicality of aggregate R&D based on equation (3). A 10% increase in real GDP growth is associated with a contemporaneous increase in aggregate R&D growth of 5.4%, and a cumulative increase of 9.8% in one year; both are significant at the 5% level. This is consistent with Barlevy (2007)'s estimate of 0.69 on the coefficient of real GDP growth when regressing aggregate R&D growth on a constant and contemporaneous real GDP growth in the U.S. from 1998 to 2003. We restrict our estimation of aggregate R&D's cyclicality to a shorter sample period, in order to compare it with the disaggregated industry results based on the 22-industry panel that covers years from 1958 to 1998 only.

Panel B of Table 3 reports the estimated cyclicality of disaggregated industry R&D based on equation (4). Column 2 and Column 3 represent the OLS estimation results without any controls: a 10% increase in industry output growth is associated with a 1.5% contemporaneous increase in industry R&D growth, and cumulatively a 2.1% increase of industry R&D growth in one year; both estimates are significant at the 1% level. Columns 4, 5, 6, and 7 of Panel B show that including industry dummies and/or year dummies as additional controls generate very similar results. Put intuitively, R&D is still pro-cyclical at the industry level, but such pro-cyclicality is much milder than that at the aggregate level. According to the point estimates, the cyclicality of industry R&D at approximately the two-digit SIC level is about 20% - 27% of that at the aggregate level.

What causes the quantitative difference between aggregate R&D's pro-cyclicality and industry R&D's pro-cyclicality presented in Table 3? Table 2 gives the explanation: at approximately the two-digit SIC level, industry R&D co-moves positively on average with output not only of its own, but also that of other industries; as a result, within-industry cyclicality of R&D is *amplified* by inter-industry R&D-output comovement, showing up at the aggregate level as a much stronger pro-cyclicality. To be more specific, the point estimates in Table 3 suggest inter-industry R&D-output comovement amplifies the cyclicality of R&D at approximately the two-digit SIC level by about five times.

4. The Schumpeterian Timing of Innovation

Two messages can be taken away from here on whether the Schumpeterian view on the timing of innovation is inconsistent with the R&D data.

First, aggregate R&D's pro-cyclicality is dominated by inter-industry R&D-output comovement, at least in the case of the U.S.. At about the two-digit SIC industry level, R&D is still pro-cyclical, as shown both by our disaggregated estimates in Panel B of Table 3 and by the positive within-industry component in Panel C of Table 2. However, we should notice that, in Table 2, the magnitude of the within-industry component *declines* as the decomposition is conducted at a more detailed industry level, so does its share in accounting for the covariance between real GDP growth and aggregate R&D growth. This points to the possibility that pro-cyclicality of industry R&D at the two-digit SIC level is still driven by co-movement across heterogeneous producers. In other words, it is possibly that, at the firm level or a more detailed industry level, R&D and output do co-vary negatively over time as the Schumpeterian view suggests, but such Schumpeterian timing is masked by co-movement of R&D and output across producers. We are not able to explore this possibility as the firm-level R&D data, based on which the NSF R&D data is compiled from, is not publicly available. But recently Aghion et al. (2010) provide evidence consistent with our hypothesis: they estimate the correlation between firm-level R&D and firm-level output approximated as sales in France, and reports the estimated coefficients to be negative under various specifications.

Secondly, Table 1 shows within-industry cyclicality of R&D differs vastly. According to the last column that reports the correlation coefficients between R&D growth and output growth for each industry category: out of the 22 industry groups at about the two-digit SIC level, six coefficients are negative and 16 are positive; the coefficient ranges from -0.3144 for Petroleum Refining (SIC 29) to 0.4594 for Electronics Equipments (SIC 366-367). This suggests the timing of innovation varies significantly across industries or entrepreneurs, and the Schumpeterian view probably captures only one of the many factor impacting the timing of innovation. Various factors have been proposed by the recent literature, including liquidity constraint by Aghion et al. (2005) and Ouyang (2010), dynamic externality inherent to the innovation process by Barlevy (2007), and cyclical persistence by Ouyang (2011). The observed vast cross-industry differences in R&D's cyclicality can be influenced by all these factors together, in addition to innovation's opportunity cost emphasized by Schumpeter (1939). Some factor can dominate others for certain industries: for example, R&D by Petroleum Refining is strictly counter-cyclical, just as the Schumpeterian view predicts; but R&D by Machinery is strongly pro-cyclical, consistent with Barlevy (2007).

In summary, we posit the conventional Schumpeterian view should be examined at the detailed industry level or at the firm level, to avoid the aggregation bias caused by inter-industry co-movement between R&D and output, and to uncover why various entrepreneurs choose the timing of innovation differently.

4. Conclusion

We decompose aggregate R&D and real GDP in the U.S. into those by 22 industry groups, and find the observed pro-cyclicality of aggregate R&D is in fact a co-movement phenomenon: 94.37% of the positive co-movement between aggregate R&D growth and real GDP growth is driven by inter-industry co-movement between industry R&D and industry output at approximately the two-digit SIC level. This result is surprising on the one hand, as the literature has never looked at the cyclicality of aggregate R&D this way. It is reasonable on the other hand, as the business cycle has long been recognized as a co-movement phenomenon itself. We estimate the cyclicality of aggregate R&D and that of industry R&D. Our results suggest inter-industry R&D-output comovement amplifies *by about five times* the cyclicality of industry R&D at about the two-digit SIC level.

We posit economists should be cautious when arguing the Schumpeterian view generates counter-factual implications on cyclical patterns of R&D only because R&D appears pro-cyclical at the aggregate level. Our result point to the possibility that firms indeed concentrate innovation when production is low as the Schumpeterian view predicts, but such Schumpeterian timing is masked by R&D-output co-movement across heterogeneous firms. Our hypothesis is consistent with the most recent evidence by Aghion et al. (2010), who estimate R&D and output are negatively correlated at the firm level in France.

Furthermore, we find within-industry cyclicality of R&D differs vastly across industries, ranging from being counter-cyclical, acyclical, to strongly pro-cyclical. We propose future research should employ detailed industry-level data or firm-level data to examine how R&D's cyclicality is affected by various factors, including innovation's opportunity cost originally proposed by Schumpeter (1939), liquidity constraint by Aghion et al. (2005), dynamic externality inherent to the innovation process by Barlevy (2007), and cyclical persistence by Ouyang (2011).

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Table 1: Disaggregated Output and R&D (1958-1998)

	R-share	Y-share	Corr (R, Y)
Aggregate	100%	100%	0.3358
Non-manufacturing	7.81%	79.48%	-0.0158
Manufacturing	92.19%	20.52%	0.4078
Non-durable manufacturing	25.65%	8.07%	-0.1413
Food (SIC 20, 21)	1.98%	2.56%	0.0741
Textiles (SIC 22m23)	0.51%	1.19%	0.1255
Paper (SIC 26)	1.08%	0.80%	-0.0787
Industrial Chemicals (SIC 281-2, 286)	11.38%	0.80%	-0.1069
Drugs (SIC 283)	3.24%	0.23%	0.2243
Other chemicals (SIC 284-5, 287-9)	2.49%	0.57%	-0.1501
Petroleum (SIC 29)	6.01%	0.43%	-0.3144
Rubber (SIC 30)	1.75%	0.41%	0.2454
Durable manufacturing	66.54%	12.45%	0.2757
Lumber (SIC 24, 25)	0.31%	0.94%	0.0193
Stone (SIC 32)	1.71%	0.87%	0.3255
Furrous Metals (SIC 331-32, 3398-99)	2.00%	1.39%	0.0327
Non-ferrous metals (SIC 333-336)	1.00%	0.50%	-0.0690
Metal Prods. (SIC 34)	2.70%	1.59%	0.1050
Machinery (SIC 35)	11.26%	2.13%	0.1627
Electronics & communication Equip. (SIC 366-367)	6.50%	0.23%	0.4594
Other Equip.(SIC 361-365, 369)	9.74%	0.73%	0.0612
Autos and Others (SIC 371, 373-75, 379)	14.39%	1.26%	0.4363
Aerospace (SIC 372,376)	8.56%	1.53%	0.3736

Scientific Instrument (SIC 381,382)	1.62%	0.34%	-0.0537
Other Instrument. (SIC 384-387)	2.42%	0.19%	0.3484
Miscellaneous manufacturing	1.54%	1.85%	0.4078

Notes: R is the R&D expenditure deflated by the GDP deflator; Y is the real value added. R-share indicates the industry share in accounting for aggregate R&D; Y-share indicates that in accounting for real GDP. Corr (R, Y) refers to the within-industry correlation between real R&D growth and output growth from 1958 to 1998. Nominal R&D series are from the NSF; the manufacturing output series are compiled from the NBER MP database, measured as real value added; non-manufacturing output series are from the BEA. See text for details.

Table 2: Decomposition of Variances and Covariance Of Aggregate R&D and Real GDP (1958-1998)

	Actual $\times 10^4$	Estimated $\times 10^4$	Within $\times 10^4$	Cross $\times 10^4$	Cross / Estimated	Average pair-wise correlation coefficients cross-industry
Panel A: Manufacturing and Non-manufacturing						
Var (Y)	4.51	5.31	3.08	2.23	42.00%	0.7317
Var (R)	11.71	12.00	12.68	-0.68	-5.67%	-0.0972
Cov (Y, R)	2.44	3.18	1.57	1.61	50.63%	0.0808
Panel B: Durable Manufacturing, Non-durable Manufacturing, and Non-Manufacturing						
Var (Y)	4.51	4.69	2.38	2.31	49.25%	0.6329
Var (R)	11.71	12.00	12.95	-0.95	-7.92%	-0.0012
Cov (Y, R)	2.44	2.86	0.25	2.61	91.25%	0.0228
Panel C: 21 Manufacturing industries and Non-manufacturing						
Var (Y)	4.51	5.47	1.94	3.52	64.35%	0.4908
Var (R)	11.71	10.45	9.03	1.42	13.56%	0.0398
Cov (Y, R)	2.44	2.82	0.16	2.66	94.37%	0.0532

Notes: R is growth in R&D expenditure deflated by the GDP deflator; Y is the real GDP growth. Var (R) is the variance in aggregate R&D growth; Var (Y) is that in real GDP growth; and Cov (Y, R) is the covariance between aggregate R&D growth and real GDP growth. The "actual" statistics are observed in the aggregate data; the "estimated" statistics are based on (2), decomposing variances and covariance into a "within-industry" component and a "cross-industry" component. Nominal R&D series are from the NSF; the manufacturing output series are compiled from the NBER MP database, measured as real value added; non-manufacturing output series are from the BEA. See text for more details.

Table 3: The Cyclicality of R&D (1959-1998): Aggregate Level and Industry Level

$$(3) R_t^A = \alpha + \beta(L) Y_t^A + \varepsilon_t$$

$$(4) R_{it} = \alpha_i + \beta(L) Y_{it} + \gamma D_t + \varepsilon_{it}$$

	No control		With industry dummies		With industry dummies and year dummies	
	L=0	*L=1*	*L=0*	*L=1*	*L=0*	*L=1*
Panel A: Aggregate R&D and Real GDP (3)						
Contemporaneous Output	0.5412** (0.2659)	0.4093 (0.2693)	-	-	-	-
Cumulative effect in one year		0.9812** (0.3320)	-	-	-	-
No. of obs.	40	39	-	-	-	-
R^2	0.1128	0.2228	-	-	-	-
Panel B: R&D and Output by 22 Industry Groups (4)						
Contemporaneous Output	0.1461*** (0.0455)	0.1229*** (0.0454)	0.1143** (0.0476)	0.0978** (0.0478)	0.1394** (0.0597)	0.1255** (0.0589)
Cumulative effect in one year	-	0.2081*** (0.0570)	-	0.1589** (0.0622)	-	0.2009*** (0.0770)
No. of obs.	880	858	880	858	880	858
R^2	0.0109	0.0136	0.1646	0.1681	0.2157	0.2201

Note: the OLS estimation of Equations (3) and (4). In Equation (3), R_t^A is the real aggregate R&D growth in year t; Y_t^A is the real GDP growth in year t. α is a constant. In equation (4), R_{it} is the real R&D growth of industry i in year t; Y_{it} is the output growth of industry i in year t. α_i is a set of industry dummies; D_t is a set of year dummies In both equations, $\beta(L)$ is a lag polynomial with lag length L. The first row in each panel presents the estimated coefficient on contemporaneous output growth; the second row reports the sum of the estimated coefficients on contemporaneous output growth and output growth lagged by one year. Robust standard errors are in parentheses; standard errors in Panel B are clustered by industry.*indicates significance at the 10% level; **significance at the 5% level; ***significance at the 1% level. See text for details.