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On the Cyclicality of R&D: Disaggregated Evidence

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This paper explores the link between short-run cycles and long-run growth by examining the cyclicality of R&D. Existing theories propose that R&D is concentrated when output is low, but aggregate data repeatedly show that R&D appears procyclical. We estimate the relationship between R&D and output at the disaggregated industry level, using an annual panel of 20 U.S. manufacturing industries from 1958 to 1998. The results indicate that R&D is in fact procyclical, but interestingly, estimates using demand-shift instruments suggest that R&D responds asymmetrically to demand shocks. We discuss the possibilities that liquidity constraints and technology improvement cause the observed procyclicality of R&D.

Key words: business cycles, economic growth, procyclicality, research and development, R&D.

JEL codes: E22, E32.

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Introduction

Lucas (1987) argues that business cycles do not matter as much as growth to economic welfare. However, macroeconomists have long recognized that cycles and growth are a unified phenomenon. For example, an opportunity-cost hypothesis has been developed by Aghion and Saint-Paul (1998) on the causal relationship from short-run cycles to long-run growth. Under this hypothesis, activities that improve long-run growth are concentrated during recessions when the opportunity cost of R&D in terms of foregone output is low; therefore, recessions have a positive impact on long-run growth by boosting growth-enhancing activities.[1] This view has also been emphasized by other authors, including Davis and Haltiwanger (1990) and Hall (1991).

While some productivity-improving activities (such as reorganization and reallocation) are observed to be concentrated during recessions, aggregate data has repeatedly shown that one of the major sources of long-run growth – research and development (hereafter R&D) – appears pro-cyclical, contrary to the prediction of the opportunity-cost hypothesis. For example, Fatas (2000), Barlevy (2004), Comin and Gertler (2006), and Walde and Woitek (2004) show that growth in aggregate R&D expenditures tracks GDP growth for the U.S. and for G7 countries. Motivated by this evidence, researchers have come to devise theoretical models to reconcile the opportunity-cost hypothesis with pro-cyclical R&D (e.g., Barlevy (2004)).

[1] The key assumption of the opportunity-cost hypothesis is that productivity-improving activities compete with production for resources so that firms concentrate such activities during periods when the returns to production are low. In contrast, Aghion and Saint-Paul (1998) also propose that, if productivity-improving activities require produced goods instead of factor inputs, then they should be pro-cyclical. However, as Griliches (1990) points out, the major input into R&D is labor, not produced goods.

This paper revisits the empirical evidence on the cyclicality of R&D, and hence on the opportunity-cost hypothesis. In particular, it examines the cyclical properties of R&D activities at the industry level, rather than in the aggregate, by estimating the relationship between R&D and output using an annual panel of 20 U.S. manufacturing industries from 1958 to 1998. This provides far more observations on the relationship between output and R&D, and avoids potential aggregation bias. The idea is to take advantage of the fact that industrial cycles are not fully synchronized with aggregate fluctuations.

The results can be summarized as follows. On the one hand, R&D is in fact pro-cyclical at the disaggregated industry level; industrial R&D commoves positively and significantly with industrial output, consistent with findings from aggregate data. At the same time, the disaggregated results lead to several other findings on what causes R&D to be pro-cyclical and on the consequences of this pro-cyclicality.

In particular, when demand-shift instruments are used to isolate the impact of demand shocks, the estimated responses are asymmetric: a demand shock that reduces output reduces R&D, while a demand shock that raises output again reduces R&D. In other words, short-run demand fluctuations, regardless of their impact on output, cause R&D to decline. These results are consistent with the opportunity-cost hypothesis with liquidity constraints. A positive demand shock for output raises the opportunity cost of R&D so that R&D declines, but a negative demand shock for output, while lowering R&D's opportunity cost, drives down the industry's representative firm's net-worth, which tightens liquidity constraints and hinders R&D. The asymmetric responses of R&D to demand shocks suggest that there is a *potential* positive impact of short-run downturns on long-run growth (as the negative response of R&D to positive demand shock suggests), but such a potential impact may be hindered by frictions such as liquidity constraints.

The rest of this paper is organized as follows. Section 2 describes the data. Section 3 compares disaggregated industry-level volatilities in R&D and output with aggregate volatilities. Evidence on pro-cyclical R&D is presented in Section 4 and 5. The asymmetric response of R&D to demand shocks is discussed in Section 6. Section 7 concludes.

Data

Two data sources are combined to examine the correlation between R&D and output at the disaggregated industry level. Data on R&D by industry is taken from the National Science Foundation (NSF), which publishes nominal R&D expenditures for 20 manufacturing industries from 1958 to 1998 based on the 1987 SIC. The NSF publishes both company-financed and federal-financed R&D; only data on the company-financed R&D are used for the purpose of this paper. The NSF suppresses some industry-year observations to avoid the disclosure of individual firms' operations. However, in all but three of these observations, they suppress either the company-financed R&D or total R&D (including federal financed), but not both. Following Shea (1998), the growth of total R&D is used to interpolate gaps in the series of company-financed R&D. Nonetheless, the interpolated values are concentrated in six industries, and the results remain robust to leaving these industries out of the analysis.[2] All the R&D series are converted into 2000 dollars using the GDP deflator. Alternative deflators from the R&D Satellite account (published by the Bureau of Economic Analysis) generate similar results. All details are available upon request.

[2] The six industries with concentrated interpolated R&D values are: Paper (SIC 26), Other Equipment (SIC 361, 364,369), Drugs (SIC 283), Other Chemicals (SIC 284, 285), Textiles (SIC 22, 23), and Lumber and Wood (SIC 24, 25).

Data on output are taken from the NBER manufacturing productivity (MP) database, which publishes data on production for 469 four-digit manufacturing industries from 1958 to 1996, and recently extended to 2002. The results are robust to leaving the extended part of the data out of the analysis. The MP data are aggregated to industries at the two-digit/three-and-a-half-digit level as defined in the R&D series. Output is measured as real value added, which equals the deflated value added using shipment-value-weighted price deflator.[3] Combining the R&D data and the MP data gives us an annual panel of R&D and output by 20 manufacturing industries covering 1958 through 1998.

We begin our empirical analysis by performing panel unit-root tests following Levin et al. (2002). All tests employ industry-specific intercepts, industry-specific time trends, and two lags. Critical values are taken from Levin et al. (2002). Results remain robust to leaving out the industry fixed effects or/and the time trend as well as to changing lag lengths. The results suggest that both the series of real R&D expenditure and real value added contain a unit root in log levels; but they are stationary in log-first differences and are not co-integrated. These results lead us to conduct all our estimations in log first differences (growth rates).

Descriptive Statistics

To facilitate our empirical investigation at the disaggregated industry level, we compare industry-level volatility of R&D and output with that at the aggregate level. During our sample period of 1958-1998, the annual growth rate of U.S. real GDP averages 3% with

[3] 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.

a standard deviation of 2.2%; the annual growth rate of aggregate company-financed real R&D expenditures averages 5% with a standard deviation of 3.5%. Table 1 summarizes the sample means and the sample standard deviations of industry-level R&D growth and output growth. The time-series plots of growth in real R&D expenditure and real output for two of the sample industries, Food (SIC 20) and Electronics & Communications Equipments (366-367), are presented in Figure 1.

Two messages can be taken away from Table 1. First, disaggregated R&D and disaggregated output display more time-series variation than the aggregate data. The annual growth rates of industrial R&D expenditures average 4.52%, close to the annual growth rate of aggregate R&D; but the standard deviations of industrial R&D average 11.56%, well above the standard deviation of aggregate R&D growth. Similarly, the annual growth rates of industrial output average 4.04%, also close to the real GDP growth; but the standard deviations of industrial output growth average 8.31%, again well above that of the annual growth of real GDP. Second, the time-series variation of R&D and output differ greatly across industries. The standard deviation of R&D growth ranges from 25.50% for Lumber and Wood (SIC 24 and 25), to 5.56% for instruments (SIC 384-387); the standard deviation of output growth ranges from 3.61% for Drugs (SIC 283) to 16.18% for Petroleum (SIC 29).

Additionally, the disaggregated industry cycles are not fully synchronized with the aggregate cycles: the time-series correlations of industrial output growth with real GDP growth range from -0.0289 for Food (SIC 20, 21) to 0.8588 for Other Equipments (SIC 361-364, 369); and the time-series correlations of industrial R&D growth with the aggregate company-financed R&D growth ranges from -0.3314 for Autos and Others (SIC 371, 373-75, 379) to 0.5108 for Aerospace (SIC 372,376).

The vast differences in these industries' time-series correlations with aggregate fluctuations, together with Table 1, suggest that fluctuations in disaggregated R&D and output do not simply reflect those shown at the aggregate level. The differences in industry-level volatilities may arise from industry-specific shocks that are of different magnitudes, or different industry responses to common aggregate shocks. Thus, the annul industry panel is used to revisit the opportunity-cost hypothesis that R&D and output commove negatively, so that R&D is concentrated during periods of low production.

Is R&D Concentrated When Production is Low?

The following relationship between the growth in R&D expenditures (R) and the growth in output (Y) is estimated:

$$(1)\quad R_{it} = \alpha + B(L)Y_{it} + \lambda f(t) + D^{92} + \varepsilon_{it},$$

where *i* indicates industry, *t* indicates year, *B(L)* is the lag polynomial operator, ε is the error term. The slope of a quadratic time trend, denoted as *f(t)*, is λ, which is allowed to differ before 1980s and afterward to capture the burst in innovation since the 1980s. Before 1992, only manufacturing industries were included in the NSF surveys for R&D. Starting from 1992, data on R&D by non-manufacturing industries were also collected. A post-1992 dummy, denoted as D^{92}, is included to capture any potential influence of this change in the process of data collection.

When (1) is estimated using OLS, the estimates of *B(L)* represent the partial correlation between R&D growth and current or lagged output growth.[4] While these partial

[4] While the causality may run from R&D to output, empirical literature has documented that R&D impacts output by long time lags; moreover, only 20% of the output of R&D (patents) lead to commercialized products (Alexopoulos (2006), Basu, Fernald, and Kimball (2006)).

correlations, in principle, may vary across industries, the common-slop coefficients on current and lagged output are imposed when estimating (1) to obtain sufficient degrees of freedom due to the short time series of annual data. Experimentations with different specifications of the model suggest that our results are robust to taking off the quadratic time trend, imposing common slopes of the quadratic time trend, allowing industry-specific time trend, including industry fixed effects, replacing the time trend with year dummies, or taking off the post-1992 dummy. Results from regressions with lag lengths of zero, one year, and two years are summarized in Table 2. Standard errors accounting for within-industry heteroskedasticity and within-industry arbitrary serial correlation are reported in parentheses.

Table 2 confirms, from the disaggregated industry data, that R&D is *not* concentrated when production is low. The estimated relationship between R&D and contemporaneous output, as Column 1 shows, is positive and significant at the 10% level. In particular, a 10% increase in output is associated with a contemporaneous increase of 1.38% in R&D. According to Column 2 and Column 3, with lagged effects considered, a 10% increase in output is associated with a contemporaneous increase in R&D of 1.3%, a cumulative increase of 2.0% in one year, and a cumulative increase of 3.0% in two years. Out of the six estimates, three are significant at 10% level, two are significant at 5% level, and one is significant at 1% level.

Apparently, these results do not support the opportunity-cost hypothesis that R&D activities are concentrated when production is low. They are consistent with findings by Fatas (2000), Barlevy (2004), Comin and Gertler (2005), and Walde and Woitek (2004), who examine aggregate data and find that R&D appears pro-cyclical for both the U.S. and for G7 countries. Table 2 shows that the opportunity-cost hypothesis fails at the disaggregated level as well.

Can Liquidity Constraints Help the Opportunity-cost Hypothesis?

One explanation of R&D is not concentrated when production is low focuses on the credit-market imperfections (Barlevy (2004), Aghion et al. (2005)). These authors argue that, due to the scarcity of credit during economic downturns, tighter liquidity constraints make it difficult to finance new or ongoing R&D activities.

One approach to test the hypothesis of liquidity constraints, which Barlevy (2004) pursues, is to identify R&D spending performed by those with non-binding constraints according to the liquid wealth of R&D-performing companies. However, it is never clear what the appropriate wealth levels are for liquidity constraints not to bind. Therefore, here we explore an alternative testable implication of liquidity constraints – they prevent R&D from increasing but not from decreasing. If the output level indicates the industry's representative firms' net-worth, so that lower output implies tighter liquidity constraints, then the opportunity-cost hypothesis should only fail in one direction. When output declines, tighter liquidity constraints prevent R&D from increasing, so that R&D tracks the decline in output; but when output increases, R&D moves in opposite direction as the opportunity-cost hypothesis suggests. Put differently, under the opportunity-cost hypothesis with liquidity constraints, the response of R&D to output should be asymmetric. [5]

[5] Note that it is likely that the liquidity constraints are binding regardless of firms' output levels. In that case, liquidity constraints are still binding even when output rises but it allows the firm to choose a R&D level closer to their desired level. However, it is then entirely the liquidity constraints that drive the cyclical property of R&D and the opportunity-cost hypothesis has no explanatory power at all. Here we try to find any evidence consistent with the opportunity-cost hypothesis with the help of liquidity constraints.

Accordingly, equation (2) is estimated allowing the coefficients on an increase in output and a decrease in output to differ, where D_{it}^{H} equals one if industry *i*'s output at time *t* is higher than its output at time *t-1* (which is the case for 45% of the sample) and equals zero otherwise; $D_{it}^{H} = 1 - D_{it}^{L}$.

(2), $R_{it} = \alpha + \beta_1 Y_{it} D_{it}^{H} + \beta_2 Y_{it} D_{it}^{L} + \lambda f(t) + D^{92} + \varepsilon_{it}$.

The results, presented in the fourth column of Table 2, again fail to support the opportunity-cost hypothesis. The estimated coefficient on a decrease in output is positive and significant at the 5% level. The estimated coefficient on an increase in output, although statistically insignificant, remains positive. One may interpret these results as that pro-cyclical R&D mainly comes from tracking declines in output, in part consistent with the liquidity-constraint hypothesis. Nevertheless, β_1 and β_2 are both positive and are quantitatively very close (around 0.14). Therefore, the opportunity-cost hypothesis fails the data again, even with the help of the liquidity constraints.

Demand-shift Instruments

A more careful examination of the opportunity-cost hypothesis suggests that there can be another reason that it appears inconsistent with data. This hypothesis looks at the cyclicality of R&D through the cyclicality of output as R&D's opportunity cost. In other words, it only captures the response of R&D to demand shocks that have no *direct* impact on R&D and affect R&D only *indirectly* through their impact on production. In reality, there may be supply shocks that affect R&D directly, so that the observed cyclical properties of R&D are driven by a mix of demand and supply shocks. In principle, appropriate demand-shift instruments can isolate the output and R&D responses to demand shocks, to see whether such shocks generate results that are consistent with the opportunity-cost hypothesis.

Aggregate-demand instruments

While finding good instruments that are both exogenous and relevant to industrial output is difficult in practice, some studies (e.g. Ramey (1991) and Shea (1993)) use aggregate output as demand-shift instruments for disaggregate industries.[6] We implement this approach, as the first step, by re-estimating equations (1) and (2) using two measures for aggregate output – real GDP and the Industrial Production Index – to instrument for industrial output. The two-stage least square estimations treat output as endogenous and employ current value for each output term and one lead of the instruments. We employ instrument lead because un-observable shocks to final demand may be first reflected as intermediate output before they are reflected in measured final output (Shea (1993a), Syverson (2004)).[7] The IV estimates of the coefficients on output in equations (1) and (2) reflect the response of R&D to output changes attributable to aggregate demand shocks approximated as aggregate output.

The results are summarized in Table 3. Panel A of Table 3 presents the results with real GDP growth as the demand-shift instrument. The IV estimates of equation (1),

[6] Other studies, such as Basu and Fernald (2006), use military spending and monetary policy to instrument for industrial activities. We do not use those because we worry that their direct impact on R&D are too strong. Military spending directly affects R&D expenditure, especially those by industries such as Aerospace. While such impact takes place through federal-financed R&D, one can expect strong correlation between federal-financed R&D and company-financed R&D due to spillovers. Monetary policy can also have a direct impact on R&D expenditure by affecting interest rate.

[7] Not surprisingly, the first-stage regressions show positive and significant correlation between output terms and instrument set. We do not employ instrument lags because first-stage regressions show that their partial correlations with the industrial output are often insignificant. Including instrument lags does not change the results qualitatively, but decreases the first-stage F-statistics and increases the second-stage standard errors. Details are available upon request.

summarized in the first three columns, are consistent with the OLS estimates: R&D responds positively to demand-driven changes in output. However, the estimates of equation (2), summarized in the fourth column, show that such positive responses mainly comes that R&D and output decline together in response to a negative demand shock (that causes output to decline). More specifically, in response to a demand shock that causes output to decline by 10%, R&D declines by 6.66%, significant at the 1% level. But, in response to a down-stream industry demand shock that *raises* output by 10%, R&D *declines* by 8.08%, significant at 10% level. Panel B of Table 3 shows that using industrial production index as demand-shift instrument returns similar results. The F-tests suggest that, for both instruments, one can reject $\beta_1 = \beta_2$.

Input-output Instruments

The results from the IV estimates employing aggregate-demand instruments are consistent with the opportunity-cost hypothesis. However, as argued earlier, aggregate output is not ideal demand-shift instruments. A good instrument is supposed to be relevant to output growth, but exogenous with R&D growth. Aggregate output is relevant but cannot be exogenous enough, especially if a large part of aggregate output fluctuations reflects common technology shocks that can have a direct impact on industrial R&D. An alternative input-output approach is proposed by Shea (1993a, 1993b) that selects demand-shift instrument by examining inter-industry factor demand linkage (Syverson (2004) and Eslava et. al. (2004)). According to Shea (1993b), a down-stream industry is considered a good instrument for an up-stream industry if it demands a large share of the up-stream industry's output (relevance criteria) but the up-stream industry comprises a relatively small share of its cost (exogeneity criteria).

Unfortunately, not all our sample industries possess input-output instruments that are relevant *and* exogenous. Demand for some industries is very diverse, so that none of their down-stream industries are truly relevant (this is the case for Industry Chemicals (SIC 281, 282, and 286)). Some other industries comprise significant cost shares, so that none of their down-stream industries are really exogenous (this is the case for Autos and Others (371, 373-75, 379)). By examining the sources of demand and cost for each of our sample industries based on Shea (1990), we find that 10 of them possess reasonably good input-output instruments. These 10 industries, the corresponding input-output instruments, and their cost-and-demand relationships are listed in Table 4; instruments data sources are described in notes to Table 4.[8] Theses 10 industries and their input-output instruments are selected according to two criteria. First, the instrument demands, either directly or indirectly, at least 12% of the industry's output. Second, the ratio of the instrument's demand share over the cost share of the two-digit sector containing the industry exceeds two. The first is supposed to promote instrument relevance, while the second is designed to promote a high ratio of instrument relevance to endogeneity. We examine the cost share of the two-digit sector containing the industry instead of the industry itself to incorporate the possibility that within-sector supply shocks are strongly correlated.

[8] Empirical literature has argued that price changes in non-manufacturing sectors are poorly measured (Shea (1998)). Therefore, we use growth in sector employment to approximate non-manufacturing output following Shea (1993a). When we tried measuring non-manufacturing IVs as growth in chain-weighted quantity measures published by the BEA, the first-stage F-statistics decrease and the second-stage standard errors increase substantially. We do not use the series of construction value put in place published by the Census to measure Construction because it starts from 1964 while our panel starts from 1958.

While input-output instruments are supposed to outperform aggregate-demand instruments in principle, they would be less useful if inter-industry comovement is driven by common aggregate shocks rather than factor demand linkages. To reduce such bias, we construct *idiosyncratic* components of input-output instruments by removing aggregate variations. More specifically, they are taken as the residual from projecting the input-output instruments on the growth in real GDP and the growth in industrial production index.

Accordingly, equations (1) and (2) are re-estimated applying input-output instruments as well as their idiosyncratic components to the restricted sample of 10 industries listed in Table 4. The two-stage least square estimations treat output as endogenous and employ current values of each output term as well as four leads of the raw or idiosyncratic input-output instruments.[9] The IV estimates of the coefficients on output therefore reflect the response of R&D to output changes attributable to (idiosyncratic) down-stream demand shocks.

The results are summarized in Table 5. Panel A presents the results employing raw input-output instruments; Panel B presents the results employing the idiosyncratic input-output instruments. The first three columns show that the IV estimates of equation (1) are different from those summarized in Table 3: R&D no longer responds positively to demand-driven changes in output. Some of the estimates are positive, some others are negative; but

[9] In contrast to the first-stage results with aggregate-demand instruments, the first-stage results with input-output instruments show that the estimated coefficients on instruments terms leading the output term by one-to-four years are statistically significant. Hence, we set the lead length of input-output instruments at four years. One may worry that such a long lead can reduce the exogeneity of the instruments. We believe that this is not problematic because: 1) the up-stream industry R&D can not impact the instruments significantly due to their low cost shares; 2) even if such bias exists, it cannot explain the main finding of the paper – the asymmetric response of R&D to demand shocks; 3) reducing the length of the instrument leads or including additional instrument lags reduce the first-stage F-statistics and increase the second-stage standard errors, but do not change the results qualitatively.

none are statistically significant. However, it is the estimates of equation (2), summarized in the fourth column, that *remain robust*: R&D responds asymmetrically to demand-driven changes in output. Panel A shows that, in response to a down-stream demand shock that reduces output by 10%, R&D declines by 4.84%; in response to a down-stream demand shock that raises output by 10%, R&D declines again by 12.50%. Panel B shows that, when aggregate variations are removed from the instruments, the asymmetric responses of R&D to demand-driven output changes become *stronger*: in response to a 10% idiosyncratic demand-driven decrease in output, R&D declines by 6.63%; in response to a 10% idiosyncratic demand-driven increase in output, it declines by 23.92%. All the estimates summarized in the fourth column, although from a much smaller sample of only 10 industries, are significant at 10% level. The F-tests suggest that, for both instruments, one can reject $\beta_1 = \beta_2$.[10]

The higher point estimates produced by idiosyncratic input-output instruments suggest that R&D responds more strongly to industry-specific demand shocks. They also imply that removing aggregate variations helps isolate the components of input-output instruments mostly likely to possess good exogeneity and relevance properties, therefore improve the IV performance by reducing aggregate-shock bias.

Liquidity Constraints, Demand Shocks, and Technological Shocks

The estimated asymmetric responses of R&D and output to demand shocks, as summarized in Table 3 and Table 5, are consistent with the opportunity-cost hypothesis with

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[10] As a further robustness check, we re-estimate equation (2) using all the demand-shift instruments in two-year growth rates to incorporate any potential lag effects. The results indicate that, the asymmetric responses of R&D to demand shocks remain qualitatively robust, although standard errors tend to increase over the two-year horizon.

liquidity constraints. R&D declines in response to a positive demand shock due to higher opportunity cost. But, in response to a negative demand shock that causes output to decline, R&D declines with output due to decreases in firms' net-worth and therefore tighter liquidity constraints. Therefore, R&D declines *always* in response to demand fluctuations. These results do not imply that R&D never increases, since they only capture R&D's response to demand shocks. As a matter of fact, the estimated correlation of R&D with an increase in output from OLS, as Table 2 shows, is positive, which suggests that other shocks are causing R&D and output to increase together.

What are the likely causes for the increases in R&D? We propose that it is positive technology shocks. The arrival of new ideas and new technology raises productivity on the one hand, and raises the return to innovation on the other hand by helping a given level of input into R&D activities to generate more ideas and technologies, so that output and R&D increase together. Moreover, given that the bulk of R&D spending is spent on development (Griliches (1990)), firms respond to the arrival of new technology developing them into further productivity gains, which also causes R&D to increase. Therefore, we interpret the results from the OLS estimations and IV estimations as implying that liquidity constraints together with technology shocks are key factors explaining the pro-cyclicality of R&D.

Interestingly, the estimated *negative* response of R&D to positive demand shocks does support the opportunity-cost hypothesis, consistent with the "virtues of bad times" proposed by Aghion and Saint-Paul (1998). Unfortunately, R&D responds differently to negative demand shocks, so that such potential virtues are not realized. And we have suggested liquidity constraints as an explanation. As a result, demand fluctuations cause R&D to decline regardless of their impact on output. It may seem natural to conclude from here that counter-cyclical fiscal policy, which aims to smooth out short-run demand fluctuations, is desirable. However, one should remain cautious in drawing such a conclusion, given the difficulty of identifying the sources of fluctuations in reality and the possibility that fiscal policy can itself be the source of demand fluctuations.[11]

Conclusion

Using a panel of 20 U.S. manufacturing industries covering 1958 through 1998, this paper explores the opportunity-cost hypothesis regarding the cyclicality of R&D at the disaggregated industry level. The results confirm that R&D is pro-cyclical. They also provide some insights on the causes and the consequences of pro-cyclical R&D. In particular, the IV estimations show that R&D declines *always* in response to demand fluctuations. We propose that liquidity constraints and technology shocks are important factors in explaining the pro-cyclicality of R&D, and that the negative impact of short-run cycles on long-run growth can mainly arise from short-run demand fluctuations.

Future empirical research should attempt to find direct evidence on the response of R&D to technology shocks. Future theoretical research should focus on devising models exploring the combined impact of liquidity constraints, demand shocks, and technology shocks on the cyclicality of R&D.

[11] Recent work by Aghion and Marinescu (2006) documents that, among OECD countries, less pro-cyclical budget policy impacts productivity growth positively, especially among countries with less financial development. This is consistent with our findings as well as suggesting that fiscal policy does cause demand fluctuations in many countries.

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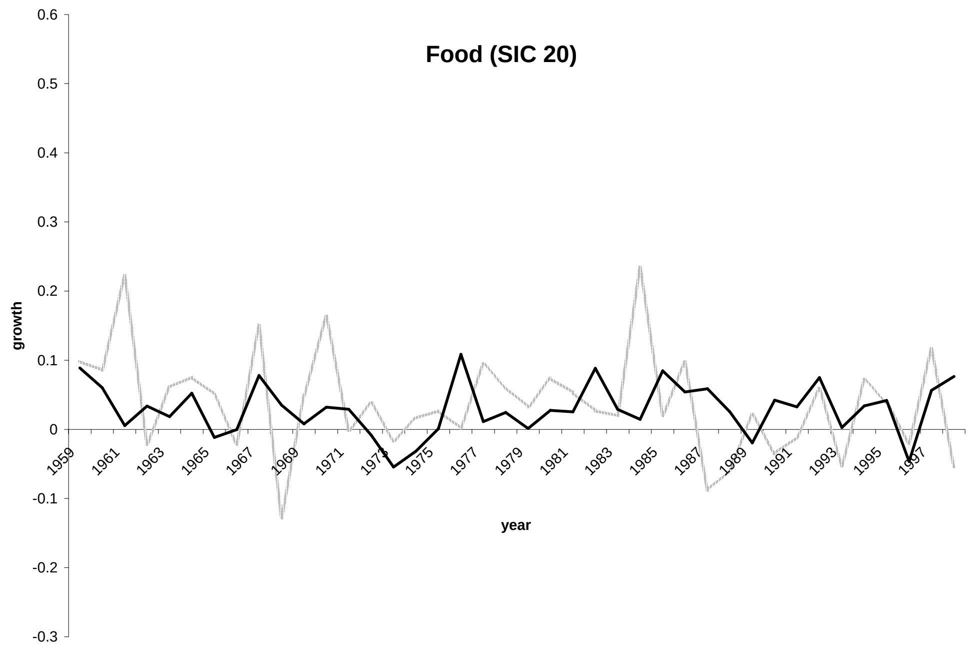
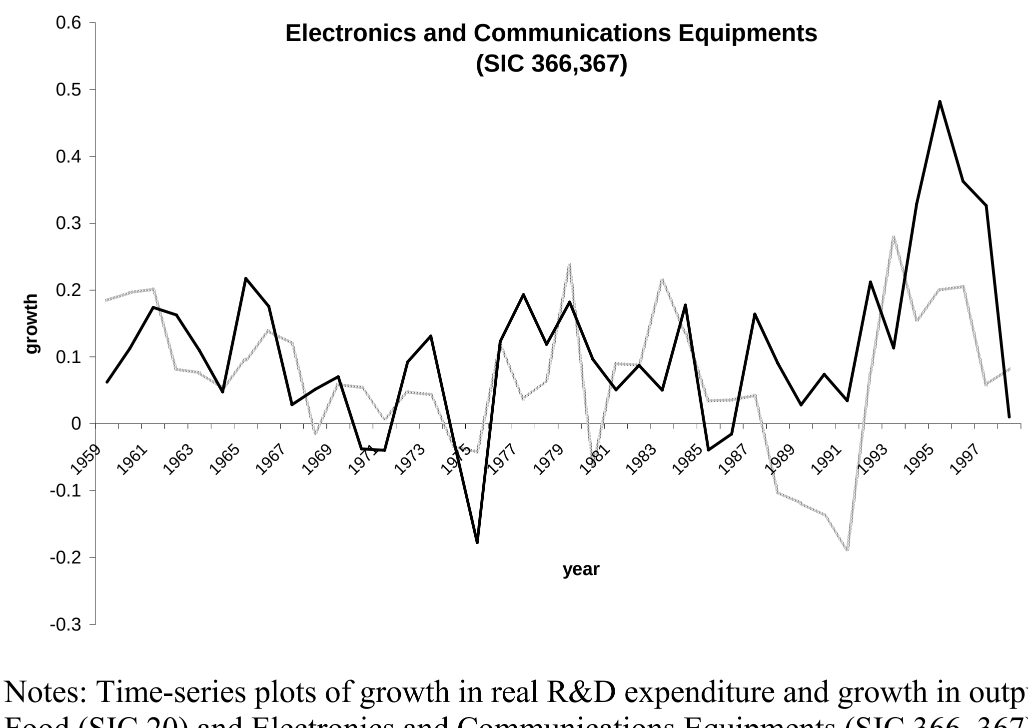
Table 1: Summary Statistics of Disaggregated Output and R&D (1958-1998)

Industry	Mean(R&D)	SD(R&D)	Mean(Y)	SD(Y)
Food (SIC 20, 21)	4.30%	8.41%	2.96%	3.72%
Textiles (SIC 22m23)	4.70%	10.37%	2.09%	4.90%
Lumber (SIC 24, 25)	3.25%	7.96%	3.18%	9.56%
paper (SIC 26)	8.05%	6.00%	5.22%	3.61%
Industrial Chemicals (SIC 281-2, 286)	4.41%	13.69%	3.59%	5.21%
Drugs (SIC 283)	1.65%	10.49%	3.11%	16.18%
other chemicals (SIC 284-5, 287-9)	4.31%	10.50%	5.26%	7.78%
Petroleum (SIC 29)	2.01%	12.08%	1.99%	6.32%
Rubber (SIC 30)	0.67%	14.43%	0.53%	12.96%
Stone (SIC 32)	1.77%	14.73%	2.25%	10.18%
Furrous Metals (SIC 331-32, 3398-99)	3.28%	11.23%	2.64%	6.59%
non-ferrous metals (SIC 333-336)	5.36%	13.30%	5.32%	9.60%
Metal Prods. (SIC 34)	7.47%	9.87%	11.02%	12.24%
Machinery (SIC 35)	7.04%	7.18%	11.02%	12.24%
Eletronics & communication Equip. (SIC 366-367)	4.57%	10.49%	3.58%	12.88%
Other Equip. (SIC 361-364, 369)	3.37%	13.11%	1.33%	9.00%
Autos and Others (SIC 371, 373-75, 379)	6.67%	13.36%	4.33%	5.97%
Aerospace (SIC 372,376)	6.94%	5.56%	5.94%	5.36%
Scientific Instrument (SIC 381,382)	5.04%	25.50%	2.36%	6.33%
Other Instrument. (SIC 384-387)	5.62%	12.98%	3.06%	5.34%
mean	**4.52%**	**11.56%**	**4.04%**	**8.30%**

Notes: Sample means and sample standard deviations of R&D growth and output growth for 20 disaggregated manufacturing industries. R&D is the growth in R&D expenditure deflated by the GDP deflator; Y is the growth in real value added. Nominal R&D by industry series are taken from the NSF; real value added series are complied from the NBER MP databases.

Figure 1: Growths in R&D and Output by Industry (1958-1998)





Notes: Time-series plots of growth in real R&D expenditure and growth in output by Food (SIC 20) and Electronics and Communications Equipments (SIC 366, 367). Solid line denotes output series, gray line denotes R&D series. See notes to Table 1 for variable definitions and data sources.

Table 2: OLS (20 Industries)

OLS1, 2, and 3: $R_{it} = \alpha + B(L)Y_{it} + \lambda f(t) + D^{92} + \varepsilon_{it}$

OLS4: $R_{it} = \alpha + \beta_1 Y_{it} D_{it}^H + \beta_2 Y_{it} D_{it}^L + \lambda f(t) + D^{92} + \varepsilon_{it}$

	OLS1	**OLS2**	**OLS3**	**OLS4**	
	Y	*Y*	*Y*	YD^H	YD^L
Contemp.	0.1384 (0.0673)*	0.1276 (0.0633)*	0.1357 (0.0642)*	0.1368 (0.1023)	0.1397 (0.0648)**
Cumulatively in one year	-	0.2062 (0.0818)**	0.1952 (0.0797)**	-	-
Cumulatively in two years	-	-	0.2965 (0.0812)***	-	-
No. of obs.	794	774	754	355 for D^H=1	439 for D^L=1
F-test $\beta_1 = \beta_2$	-	-	-	0.00 (*p*=0.9781)	
R-squared	0.0350	0.0369	0.0392	0.0350	

Notes: OLS estimates of the relationship between real R&D expenditure and output, using data on 20 manufacturing industries from 1958 to 1998. All estimations are conducted in growth rates. R_{it} represents R&D and Y_{it} represents output of industry *i* in year *t*; *f(t)* is a quadratic time trend, and λ is allowed to differ before and after the 1980s; D^{92} is a post-1992 dummy. OLS1, OLS2, and OLS3 correspond to estimations with lag length of zero, one year, and two years. OLS4 correspond to zero lag allowing coefficient on an increase in output and a decrease in output to vary. D_{it}^H equals one if industry *i*'s output in year *t* is higher than its output in year *t-1* and equals zero otherwise; $D_{it}^H = 1 - D_{it}^L$. Standard errors controlled for within-industry heteroskedasticity and within-industry arbitrary serial correlation are reported in parentheses. A (*) indicates significance at 10%; a (**) indicates significance at 5%; and a (***) indicates significance at 1%.

Table 3: Aggregate-demand IVs (20 industries)

IV1, 2, and 3: $R_{it} = \alpha + B(L)Y_{it} + \lambda f(t) + D^{92} + \varepsilon_{it}$

IV4: $R_{it} = \alpha + \beta_1 Y_{it} D_{it}^{H} + \beta_2 Y_{it} D_{it}^{L} + \lambda f(t) + D^{92} + \varepsilon_{it}$

	IV1	IV2	IV3	IV4	
No. of obs.	794	774	754	355 for D^H=1	439 for D^L=1
Panel A: Real GDP as IV					
	Y	Y	Y	YD^H	YD^L
Contemp.	0.1617 (0.0804)*	0.1625 (0.0865)*	0.1823 (0.0908)*	-0.8079 (0.4044)*	0.6657 (0.2337)***
Cumulatively in one year	-	0.2348 (0.1176)*	0.2340 (0.1176)*	-	-
Cumulatively in two years	-	-	0.3136 (0.1300)**	-	-
F-test $\beta_1 = \beta_2$	-	-	-	5.87 (p=0.0255)	
Panel B: Industrial Production as IV					
	Y	Y	Y	YD^H	YD^L
Contemp.	0.1231 (0.0715)*	0.1243 (0.0780)	0.1705 (0.0903)*	-0.6561 (0.3341)*	0.5761 (0.2026)***
Cumulatively in one year	-	0.1945 (0.0923)**	0.2086 (0.0929)**	-	-
Cumulatively in two years	-	-	0.3267 (0.1252)**	-	-
F-test $\beta_1 = \beta_2$				5.91 (p=0.0251)	

Notes: IV estimates of the relationship between real R&D expenditure and output, using data on 20 manufacturing industries from 1958 to 1998, real GDP series from the BEA, and Industrial Production Index from the Federal Reserve Board. The two-stage least squares estimations treat output as endogenous and using real GDP and industrial production to instrument for industrial output. IV1, IV2, and IV3 correspond to estimations with lag length of zero, one year, and two years. IV4 correspond to zero lag allowing coefficient on an increase in output and a decrease in output to vary. IV1 and IV4 regressions employ the current value and leads of instruments; IV2 employ an additional one-year lag, and IV3 employ additional one-year and two-year lag of the instruments. All estimations are conducted in growth rates. See notes to Table 2 for more specifications.

Table 4: Industries and Their Input-Output Instruments

Industry	Down-stream industry	DS	CS
Lumber (SIC 24, 25)	Total Construction	53.9%	8.3%
paper (SIC 26)	Food (SIC 20)	15.5%	4.1%
Drugs (SIC 283)	Health Care	23.7%	4.5%
other chemicals (SIC 284-5, 287-9)	Agriculture	15.6%	7.7%
Petroleum (SIC 29)	Total Construction	12.94%	2.7%
Rubber (SIC 30)	Transportation (SIC 37)	21.1%	4.6%
Stone (SIC 32)	Total construction	41.9%	6.5%
Furrous Metals (SIC 331-32, 3398-99)	Total construction	24.84%	12.20%
non-ferrous metals (SIC 333-336)	Total construction	24.85%	12.20%
Other Equip. (SIC 361-364, 369)	Total construction	15.06%	5.00%

Notes: industries, the input-output instruments, and their cost-and-demand relationships. DS is the share of the up-stream industry's output demanded by the down-stream industry, either directly or through other intermediate links; CS is the cost share of the down-stream industry originating from the two-digit sector that contains the up-stream industry, either directly or through other intermediate links. Food (SIC 20) and Transportation (SIC 37) are measured as growth in real value added constructed from the MP databases. Health Care, Agriculture, Total Construction are measured as growth in sector employment published by the BEA. See text for more explanations.

Table 5: Input-output IVs (10 industries)

IV1, 2, and 3: $R_{it} = \alpha + B(L)Y_{it} + \lambda f(t) + D^{92} + \varepsilon_{it}$

IV4: $R_{it} = \alpha + \beta_1 Y_{it} D_{it}^H + \beta_2 Y_{it} D_{it}^L + \lambda f(t) + D^{92} + \varepsilon_{it}$

	IV1	IV2	IV3	IV4	
No. of obs.	396	386	376	183 for D^H=1	213 for D^L=1
Panel A: input-output IV					
	Y	Y	Y	YD^H	YD^L
Contemp.	-0.0188 (0.0994)	0.0462 (0.1160)	0.0347 (0.1240)	-1.2498 (0.6394)*	0.4838 (0.3395)*
Cumulatively in one year	-	0.006 (0.1227)	0.0260 (0.1273)	-	-
Cumulatively in two years	-	-	0.2353 (0.2575)	-	-
F-est $\beta_1 = \beta_2$	-	-	-	3.78 (p=0.0837)	
Panel B: idiosyncratic input-output IV					
	Y	Y	Y	YD^H	YD^L
Contemp.	-0.1836 (0.1203)	-0.3977 (0.2917)	-0.5483 (0.5563)	-2.3918 (1.1311)*	0.6627 (0.3606)*
Cumulatively in one year	-	0.0224 (0.1358)	0.0432 (0.2202)	-	-
Cumulatively in two years	-	-	-0.3036 (0.5028)	-	-
F-test $\beta_1 = \beta_2$	-	-	-	4.92 (p=0.0538)	

Notes: IV estimates of the relationship between real R&D expenditure and output, using data on 10 manufacturing industries listed in Table 4 from 1958 to 1998. The two-stage least squares estimations treat output as endogenous and using raw and idiosyncratic input-output instruments to instrument for industrial output. IV1 and IV4 regressions employ current value and instrument leads; IV2 employs an additional one-year lag, and IV3 employs additional one-year and two-year lags of the instruments. All estimations are conducted in growth rates. See notes to Table 2 and Table 3 for more details on modeling specifications; see notes to Table 4 for sample industries and their input-output instruments; see text for more details.

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