ON THE CYCLICALITY OF R&D

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Abstract—We explore 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 using an annual panel of twenty 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 it responds asymmetrically to demand shocks. We propose that liquidity constraint is an important cause for the observed procyclicality of R&D.

I. 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. According to this hypothesis, activities that improve long-run growth are concentrated during downturns when the opportunity cost of R&D in terms of forgone output is low, so that recessions have a positive impact on long-run growth by boosting growth-enhancing activities.[1] This view traces back to Joseph Schumpeter (1939) and has 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 have repeatedly shown that one of the major sources of long-run growth, research and development, appears procyclical. 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 United States and for G7 countries. Motivated by such evidence, researchers have come to devise theoretical models to reconcile the opportunity cost hypothesis with procyclical R&D (Barlevy, 2007).

This paper revisits the empirical evidence on the cyclicality of R&D and, hence, on the opportunity cost hypothesis. In particular, it explores the cyclical properties of R&D at the industry level rather than in the aggregate. This provides far more observations on the relationship between output and R&D and avoids potential aggregation bias. We are motivated by the fact that industry cycles are not perfectly synchronized with aggregate fluctuations. Some industries lead, while others lag the aggregate cycle. If an industry's downturns happen to coincide with aggregate booms, then its R&D could appear procyclical over the aggregate cycle dominated by other industries' activities, even if its R&D is concentrated during its own downturns. Therefore, procyclical aggregate R&D may arise from an aggregation bias rather than reflecting how firms balance production and innovation intertemporally.

To reduce potential aggregation bias, we examine the cyclicality of R&D employing an annual panel of twenty U.S. manufacturing industries from 1958 to 1998. Our findings are as follows. On the one hand, R&D is in fact procyclical at the industry level; industrial R&D co-moves positively and significantly with industrial output. However, the disaggregated procyclicality turns out much milder than that suggested by aggregate data. More importantly, the disaggregated results lead to several other findings on what causes R&D to be procyclical and on the consequences of this procyclicality.

In particular, when demand-shift instruments are used to isolate the impact of demand shocks from other supply shocks that can affect R&D directly, the estimated responses turn out 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 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. We thus propose liquidity constraints as a key factor in explaining the procyclicality of R&D, and provide further evidence on how liquidity constraints influence R&D's cyclicality with data on industrial balance sheets.

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[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 procyclical. However, as Griliches (1990) points out, the major input into R&D is labor, not produced goods.

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The rest of this paper is organized as follows. Section II describes the data. Section III estimates the cyclicality of disaggregate R&D over industry-specific cycles. The instrumental variable (IV) approach is applied in section IV. Section V examines the liquidity constraint hypothesis with data on industrial balance sheets. Section VI concludes.

II. 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 are taken from the National Science Foundation (NSF), compiled from the Survey of Industrial Research and Development (SIRD), conducted jointly by the NSF and the U.S. Census Bureau. Data on output are taken from the NBER manufacturing productivity (MP) database, compiled from the Annual Survey of Manufacturers (ASM) conducted by the Census Bureau. The sample of SIRD is drawn from the Standard Statistical Establishment List (SSEL), which is also used by the Census Bureau to track the identity of manufacturers in the ASM. This implies a reasonably good match of the two data sets when they are combined.

Data on R&D by industry provide R&D expenditures for twenty two-digit and three-and-a-half digit manufacturing industries from 1957 to 1998 based on the 1987 Standard Industry Classification (SIC) system.[2] The NSF publishes both company-financed and federal-financed R&D; only data on the company-financed R&D are used in this paper. 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 (including federal financed) is suppressed, 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.[3] All of the R&D series are converted into 2000 dollars using the GDP deflator (Barlevy, 2007). Alternative deflators from the R&D satellite account published by the Bureau of Economic Analysis generate similar results. (All details are available on request.)

The MP databases publish data on production for 469 four-digit manufacturing industries from 1958 to 1996, and recently extended to 2005. 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 and the combination of three-digit level as defined in the R&D series. Output is measured as real value added, as the deflated value added using shipment-value-weighted price deflator.[4] Combining the R&D data and the MP data gives us an annual panel of R&D and output by twenty manufacturing industries covering 1958 through 1998.

We begin our empirical analysis by performing panel unit-root tests following Levin, Lin, and Chu (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 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).

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 averaged 3.45% with a standard deviation of 2.10%; the annual growth rate of aggregate company-financed real R&D expenditures averaged 5.37% with a standard deviation of 3.38%. Table 1 summarizes the sample means and the sample standard deviations of industry-level R&D growth and output growth.

Two messages can be taken away from table 1. First, R&D and output are much more volatile at the disaggregated industry level: the standard deviations of industrial R&D growth average 11.14%, and those of industrial output growth average 8.06%, both about four times those in the aggregate data. Second, variations in R&D and output differ greatly across industries. The standard deviation of R&D growth ranges from 25.12% for Lumber (SIC 24 and 25), to 4.82% for Drugs (SIC 283); that of output growth ranges from 16.18% for Petroleum Refining (SIC 29) to 3.61% for Drugs (SIC 283).

Moreover, the disaggregate industry cycles are not fully synchronized with the aggregate cycle: 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 Equipment (SIC 361-364, 369). 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 annual industry panel is used to revisit the opportunity cost hypoth-

[2] Starting in 1999, industries have been defined according to the North American Industry Classification System (NAICS).

[3] 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 (SIC 24, 25).

[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 on request.

TABLE 1.—SUMMARY STATISTICS OF DISAGGREGATED OUTPUT AND R&D (1958–1998)

Industry	Mean (R)	S.d. (R)	Mean (Y)	S.d. (Y)
Food (SIC 20, 21)	3.88%	7.54%	2.96%	3.72%
Textiles (SIC 22, 23)	4.31	10.91	2.09	4.90
Lumber (SIC 24, 25)	4.62	25.12	2.36	6.33
Paper (SIC 26)	5.20	12.10	3.06	5.34
Industrial Chemicals (SIC 281–282, 286)	2.83	6.93	3.18	9.56
Drugs (SIC 283)	7.63	4.82	5.22	3.61
Other Chemicals (SIC 284–285, 287–289)	3.99	12.19	3.59	5.21
Petroleum Refining (SIC 29)	1.23	8.97	3.11	16.18
Rubber (SIC 30)	3.94	10.50	5.26	7.78
Stone (SIC 32)	1.59	12.40	1.99	6.32
Furrous Metals (SIC 331–332, 3398, 3399)	0.25	14.06	0.53	12.96
Non-ferrous Metals (SIC 333–336)	1.35	14.37	2.25	10.18
Metal Prods. (SIC 34)	2.86	10.94	2.64	6.59
Machinery (SIC 35)	4.94	13.06	5.32	9.60
Eletronics Equipment (SIC 366–367)	7.05	10.49	11.02	12.24
Other Equipment (SIC 361–365, 369)	1.88	12.77	3.16	7.39
Autos and Others (SIC 371, 373–375, 379)	4.15	6.82	3.58	12.88
Aerospace (SIC 372,376)	2.95	12.52	1.33	9.00
Scientific Instrument (SIC 381,382)	6.25	11.18	4.33	5.97
Other Instrument. (SIC 384–387)	6.52	5.18	5.94	5.36
Cross-industry mean	3.87	11.14	3.64	8.06
Aggregate economy	5.37	3.38	3.45	2.10

R is the growth in R&D expenditure deflated by the GDP deflator; Y is the growth in real value added. *Mean*(R), *SD*(R), *Mean*(Y), and *SD*(Y) are the sample means and sample standard deviations of R&D growth and output growth for twenty disaggregated manufacturing industries. Nominal R&D by industry series are taken from the NSF; real value-added series are complied from the NBER MP databases. See text for more details.

esis that R&D and output co-move negatively so that R&D is concentrated during periods of low production.

III. The Cyclicality of Disaggregated R&D

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

$$R_{it} = \alpha + B(L)Y_{it} + \lambda_1 D_t^{pre80} f(t) + \lambda_2 D_t^{post80} f(t) + \gamma D^{92} + \varepsilon_{it}, \quad (1)$$

where i indicates industry, t indicates year, $B(L)$ is the lag polynomial operator, and ε is the error term. D_t^{pre80} is a pre-1980 dummy and D_t^{pre80} is a post-1980 dummy. λ_1 and λ_2 are 1-by-2 vectors that capture the slopes of a quadratic time trend $f(t) = (t,t^2)'$. We allow the slopes before and after 1980 to differ because the R&D series display a jump in trend around 1980 for most of the industries.[5] We also include a post-1992 dummy, D^{92}, to capture the potential influence of a change in the R&D data collection process as, starting from 1992, the NSF lowered the criteria on employer size in SIRD.

When equation (1) is estimated using OLS, the estimates of $B(L)$ represent the partial correlation between R&D growth and current or lagged output growth.[6] While these partial correlations in principle may vary across industries, the common-slope coefficients on current and lagged output are imposed when estimating equation (1) to obtain sufficient degrees of freedom due to the short time-series length 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, including lagged growth in R&D, replacing the time trend with year dummies, taking off the post-1992 dummy, or letting the post-1992 dummy to interact with the output coefficient. The maximum output lag length is set at two years, both because the cumulative impact of output often peaks in two years, and because the estimated coefficient on output growth lagged more than two years is usually statistically insignificant.

A. *Procyclical Industrial R&D*

Results from estimations of equation (1) 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.

[5] In all the regressions conducted in this paper, the estimated coefficient on the post-1980 trend stays statistically significant at the 1% level. Imposing the same quadratic time trend throughout the sample period otherwise would produce insignificant estimates on the trend as well as raise the standard errors. There are potentially two explanations for the trend change around 1980: it is likely related to the drop in aggregate volatility referred to as the Great Moderation; and it may be caused by a burst in innovations driven by a change in the patent approval policy at the U.S. Patent and Trademark Office at the time, shown as a dramatic increase in patent examiners (McConnell & Perez-Quiros, 2000; Griliches, 1990).

[6] While the causality may run from R&D to output, empirical literature has documented that R&D has an impact on output by long time lags, and only 20% of the outcome of R&D (patents) can actually contribute to later commercialized products (Alexopoulos, 2006; Basu, Fernald, & Kimball, 2006).

TABLE 2.—OLS

	Equation (1)[a]			Equation (2)[b]	
	Y	Y	Y	YD^H	YD^L
Contemporaneous	0.1351 (0.0672)*	0.1222 (0.0623)*	0.1299 (0.0626)*	0.1246 (0.1035)	0.1440 (0.0652)**
Cumulatively in one year	-	0.2126 (0.0810)**	0.2031 (0.0788)**	-	-
Cumulatively in two years	-	-	0.2980 (0.0805)***	-	-
Observations	794	774	754	358 for $D_H = 1$	436 for $D_L = 1$
F-test, $\beta_1 = \beta_2$	-	-	-	0.04 ($p = 0.8532$)	
R^2	0.0364	0.0394	0.0411	0.0364	

OLS estimates of the relationship between real R&D expenditure and output using data on twenty manufacturing industries from 1958 to 1998. All estimations are conducted in growth rates. See text for explanation of equations. Standard errors controlled for within-industry heteroskedasticity and within-industry arbitrary serial correlation are reported in parentheses. *significance at 10%; **significance at 5%; ***significance at 1%.

[a]Estimations of equation (1) with lag length of 0, 1 year, and 2 years.

[b]Estimations of equation (2) with 0 length allowing the coefficient on an increase in output and a decrease in output to vary.

TABLE 3.—AGGREGATE-DEMAND IVS (TWENTY INDUSTRIES)

				IV2	
Observations	794	774	754	358 for D^H=1	436 for D^L=1
			A: Real GDP as IV		
	Y	Y	Y	YD^H	YD^L
Contemporaneous	0.1540 (0.0804)*	0.1516 (0.0859)*	0.1688 (0.0878)*	−0.8659 (0.4434)*	0.6831 (0.2500)**
Cumulatively in one year	-	0.2425 (0.1171)*	0.2434 (0.1165)*	-	-
Cumulatively in two years	-	-	0.3108 (0.1286)**	-	-
F-test $\beta_1 = \beta_2$	-	-	-	5.42 ($p = 0.0311$)	
			B: Industrial Production as IV		
	Y	Y	Y	YD^H	YD^L
Contemporaneous	0.1172 (0.0712)	0.1144 (0.0767)	0.1545 (0.0840)*	−0.7519 (0.3715)*	0.6221 (0.2281)**
Cumulatively in one year	-	0.2058 (0.0928)**	0.2200 (0.0937)**	-	-
Cumulatively in two years	-	-	0.3246 (0.1240)**	-	-
F-test $\beta_1 = \beta_2$				5.77 ($p = 0.0267$)	

IV estimates of the relationship between real R&D expenditure and output, using data on twenty manufacturing industries from 1958 to 1998, real GDP series from the Bureau of Economic Analysis, and the industrial production index from the Federal Reserve Board. The two-stage least-square estimations treat output as endogenous and using real GDP and industrial production to instrument for industrial output. Each IV regression employs the current value and at least a one-year lead of the instruments for each output term. See notes to table 2 for more specifications.

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 1.35% in R&D. According to columns 2 and 3, with lagged effects considered, a 10% increase in output is associated with a contemporaneous increase in R&D of 1.22%, a cumulative increase of 2.13% in one year, and a cumulative increase of 2.98% in two years. Out of the six estimates, three are significant at the 10% level, two are significant at the 5% level, and one is significant at the 1% level.

Apparently the results in table 2 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, 2007), Comin and Gertler (2006), and Walde and Woitek (2004), who examine aggregate data and find that R&D appears procyclical for both the United States and for G7 countries. However, the estimated R&D's procyclicality in table 2 is much milder than that documented previously using the aggregate data. For example, Barlevy (2007) estimates the partial correlation between real GDP growth and aggregate R&D growth in the U.S. to be 0.69. According to table 2, this partial correlation at the industry level is only 0.1351, less than one-fifth of Barlevy's estimate.

B. Can Liquidity Constraints Help the Opportunity Cost Hypothesis?

One explanation of why R&D is not concentrated when production is low focuses on credit market imperfections. Barlevy (2007) and Aghion et al. (2005) 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.

Barlevy (2004) tests the liquidity constraint hypothesis by examining the cyclicality of R&D performed by companies whose constraints are less likely to bind. However, it is never clear what the appropriate wealth levels are for liquidity constraints not to bind. Therefore, we explore an alternative testable implication of liquidity constraints. That is, they prevent R&D from increasing but not from decreasing. If the output level reflects an industry's representative firm's net worth, so that lower output implies tighter liquidity constraints, then the opportunity cost hypothesis should fail in only 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 the 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.[7]

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 0 otherwise; $D_{it}^H = 1 - D_{it}^L$:

$$R_{it} = \alpha + \beta_1 Y_{it} D_{it}^H + \beta_2 Y_{it} D_{it}^L + \lambda_1 D_t^{pre80} f(t) + \lambda_2 D_t^{post80} f(t) + \gamma D^{92} + \varepsilon_{it}. \quad (2)$$

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 procyclical 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 quantitatively very close (around 0.13). The F-tests suggest that one cannot reject $\beta_1 = \beta_2$. Therefore, the opportunity cost hypothesis fails the data again, even with the help of liquidity constraints.

IV. Demand-Shift Instruments

A more careful examination of the opportunity cost hypothesis suggests 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 captures the response of R&D to demand shocks that have no direct impact on R&D and that affect R&D 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. Therefore, in principle, appropriate demand-shift instruments can isolate the output and R&D responses to demand shocks to see whether such shocks generate results consistent with the opportunity cost hypothesis.

A. Aggregate-Demand Instruments

While finding good instruments that are both perfectly exogenous and substantially relevant to industrial output is difficult in practice, some studies (Ramey, 1991; Shea, 1993a, 1993b) use aggregate output as demand shift instruments for disaggregated industries. We implement this approach to capture how industrial R&D and output respond to aggregate shocks and as the first step to apply the IV approach. We estimate equations (1) and (2) again, using two measures for aggregate output—real GDP and the industrial production index—to instrument for industrial output. The two-stage least-square treat output as endogenous and employ current value and at least one lead of the instruments for each output term. We employ the instrument lead because unobservable shocks to final demand may be first reflected as intermediate output before they are reflected in measured final output (Shea, 1993a; Syverson, 2004).[8] 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), 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 stem from the fact 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%,

[7] 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 an R&D level closer to their desired level. However, it is then entirely 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.

[8] Not surprisingly, the first-stage regressions show a positive and significant correlation between output terms and the instrument set. We do not employ instrument lags because the 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 on request.

TABLE 4.—INDUSTRIES AND INPUT-OUTPUT INSTRUMENTS

Industry	Downstream Industry	Demand Share	Cost Share
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 284–285, 287–289)	Agriculture	15.6	7.7
Petroleum Refining (SIC 29)	Total Construction	12.94	2.7
Rubber (SIC 30)	Transportation Equipments (SIC 37)	21.1	4.6
Stone (SIC 32)	Total Construction	41.9	6.5
Ferrous Metals (SIC 331–332, 3398–3399)	Total Construction	24.84	12.20
Non-ferrous Metals (SIC 333–336)	Total Construction	24.85	12.20
Other Equipment (SIC 361–364, 369)	Total Construction	15.06	5.00

Industries, the input-output instruments, and their cost and demand relationships. Demand share is the share of the upstream industry's output demanded by the downstream industry, either directly or through other intermediate links. Cost share is the cost share of the downstream industry originating from the two-digit sector that contains the upstream industry, either directly or through other intermediate links. Food (SIC 20, 21) and Transportation (SIC 37) are measured as growth in real value added constructed from the MP database. Health Care, Agriculture, Total Construction are measured as growth in sector employment published by the Bureau of Economic Analysis. This table is generated based on Shea (1990). See text for details.

R&D declines by 6.83%, significant at the 5% level. But in response to a demand shock that raises output by 10%, R&D declines again by 8.66%, significant at the 10% level. Panel B of table 3 shows that using the industrial production index as the demand shift instrument returns similar results. The F-tests suggest that for both instruments, one can reject $\beta_1 = \beta_2$.

B. *Input-Output Instruments*

The results from the IV estimates employing aggregate demand instruments are consistent with the opportunity cost hypothesis with liquidity constraints. However, aggregate output cannot be ideal demand-shift instruments. A good instrument is supposed to be relevant to output growth but exogenous to R&D growth. Aggregate output is relevant yet not exogenous, especially if a large part of aggregate output fluctuations reflects common supply shocks that affect industrial R&D directly or if industry supply shocks have aggregate impacts through interindustry linkages.

Shea (1993b) proposes an alternative input-output approach that selects demand-shift instruments by examining interindustry factor demand linkages (Syverson, 2004; Eslava et al., 2004). According to Shea (1993b), the output of a downstream industry A is considered a good instrument for an upstream industry B if two conditions are satisfied: (1) A demands a large proportion of B's output, so that A's output is relevant to B, and (2) B, together with other closely related industries, comprise a small share of A's cost, so that A is exogenous to B. For example, the output of Health Care is considered a good instrument for Drugs if Health Care covers a large share of the demand for Drugs output, while Drugs, together with other industries of Chemicals, takes a small share of Health Care cost.

Unfortunately, not all our sample industries possess input-output instruments that are relevant and exogenous. Demand for some industries, such as industry Chemicals (SIC 281, 282, and 286), is so diverse that none of their downstream industries demand enough of their output to be truly relevant. Some other industries, like Autos and Others (SIC 371, 373–375, 379), comprise significant cost shares of all of their demanders, so that any downstream industries' output cannot be that exogenous. Based on Shea (1990), we carefully examine the sources of demand and cost for each of our sample industries, and find that ten of them possess reasonably good input-output instruments. These ten industries, together with their input-output instruments and cost-demand relationships, are listed in table 4; the instruments data sources are described in the notes to table 4.[9] The input-output instruments for these 10 industries are selected according to two criteria. First, the instrument industry demands, either directly or indirectly, at least 10% of the industry's output. Second, the share of the industry's output demanded by the instrument industry (demand share) is at least twice as much as the share of the instrument industry's production cost (cost share) in the two-digit sector containing the instrumented industry. The first criterion ensures instrument relevance, while the second promotes exogeneity through a high ratio of instrument relevance to endogeneity. The cost share of the entire two-digit sector is examined to incorporate the possibility that within-sector supply shocks are strongly correlated.

While input-output instruments are supposed to outperform aggregate-demand instruments in principle, they would be less useful if the co-movement between our sample industries and their instrument industries 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

[9] The empirical literature has argued that price changes in nonmanufacturing sectors are poorly measured (Shea, 1998). Therefore, we use growth in sector employment to approximate nonmanufacturing output, following Shea (1993a). When we tried measuring nonmanufacturing 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 Bureau because it starts in 1964, while our panel starts in 1958.

TABLE 5.—INPUT-OUTPUT IVS: TEN INDUSTRIES

	Equation (1)			Equation (2)	
Observations	396	386	376	186 for D^H=1	210 for D^L=1
A: Input-Output IV					
	Y	Y	Y	YD^H	YD^L
Contemporaneous	−0.0122	−0.0620	0.0047	−1.1848	0.4767
	(0.1004)	(0.1196)	(0.1090)	(0.6422)*	(0.2428)*
Cumulatively in one year	-	0.0725	0.0653	-	-
		(0.1358)	(0.1267)		
Cumulatively in two years	-	-	0.2395	-	-
			(0.2630)		
F-test $\beta_1 = \beta_2$	-	-	-	3.85 ($p = 0.0814$)	
B: Idiosyncratic Input-Output IV					
	Y	Y	Y	YD^H	YD^L
Contemporaneous	−0.1738	−0.4181	−0.6365	−2.2899	0.6656
	(0.1194)	(0.3055)	(0.5425)	(1.0675)*	(0.3544)*
Cumulatively in one year	-	0.0479	0.0839	-	-
		(0.1487)	(0.2231)		
Cumulatively in two years	-	-	−0.3342	-	-
			(0.4892)		
F-test $\beta_1 = \beta_2$	-	-	-	4.99 ($p = 0.0524$)	

IV estimates of the relationship between real R&D expenditure and output, using data on ten manufacturing industries listed in table 4 from 1958 to 1998. The two-stage least-square estimations treat output as endogenous and use raw and idiosyncratic input-output instruments to instrument for industrial output. Each regression employs current value and at least four leads of the instrument for each output term. All estimations are conducted in growth rates. See the text and notes to Tables 2 and 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.

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 estimated applying input-output instruments as well as their idiosyncratic components to the restricted sample of ten 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. The IV estimates of the coefficients on output therefore reflect the response of R&D to output changes attributable to raw or idiosyncratic downstream demand shocks. We set the lead length at four years, as the first-stage regression results show that the estimated coefficient on the four-year lead of the input-output instruments is statistically significant for output decreases. Changing the lead length produces quantitatively similar estimates but tends to raise the standard errors of the second-stage regression.

The results are summarized in table 5. Panel A presents the results applying raw input-output instruments; panel B presents those employing idiosyncratic input-output instruments. The IV estimates of equation (2), summarized in the first three columns, are different from those in table 3: R&D no longer responds positively to demand-driven changes in output. Some of the estimates are positive and some others negative, but 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 output fluctuations. Panel A shows that, in response to a downstream demand shock that reduces output by 10%, R&D declines by 4.77%; in response to a downstream demand shock that raises output by 10%, R&D declines again by 11.85%. In panel B when aggregate variations are removed from the instruments, the asymmetric responses of R&D to demand-driven output changes become even stronger: in response to a 10% idiosyncratic demand-driven decrease in output, R&D declines by 6.66%; in response to a 10% idiosyncratic demand-driven increase in output, it declines by 22.90%. All the estimates summarized in the fourth column, although from a much smaller sample of only ten industries, are significant at the 10% level. The F-tests suggest that for both instruments, one can reject $\beta_1 = \beta_2$.[10]

A cautionary note should be made. Table 4 suggests that, for six out of the ten industries, industrial output is instrumented by Total Construction output when applying the input-output IV approach. This implies a sample heavily weighted toward construction material industries, and raises the question of how representative our results are. However, it is difficult to argue theoretically why construction material industries should feature stronger R&D elasticity. Moreover, the ten-industry sample also contains nonconstruction-related industries, such as Paper (SIC 26), Drugs (SIC 283), and Rubber (SIC 37), instrumented correspond-

[10] As a robustness check, we 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. Details are available on request.

TABLE 6.—INDUSTRIAL FINANCIAL INDICATORS AND AVAILABILITY OF INPUT-OUTPUT IV

Industries Ranked by Liquid Assets	Liquid Assets (million$)	Net Worth (million$)	Does This Industry Possess Valid Input-Output IV?
Petroleum Refining (SIC 29)	14,754.12*	18,3509.58*	Yes
Machinery (SIC 35)	16,245.76*	13,2198.96*	No
Food (SIC 20, 21)	11,745.77*	10,1281.77*	No
Industry Chemicals (SIC 281–282, 286)	43,86.66	63,445.07	No
Metal Products (SIC 34)	6,419.81	4,8729.80	No
Paper (SIC 26)	3,330.01	4,8464.70	Yes
Drugs (SIC 283)	5,833.92	4,2115.68	Yes
Furrous Metals (SIC 331–332, 3398–3399)	6,113.51	40,692.58	Yes
Other Chemicals (SIC 284–285, 287–289)	5,602.33	40,025.26	Yes
Non-Ferrous Metals (SIC 333–336)	2,684.52	33,835.19	Yes
Aerospace (SIC 372, 376)	4,790.98	33,411.20	No
Stones (SIC 32)	3,611.92	31,138.11	Yes
Rubber (SIC 30)	2,482.09	24,718.18	Yes
Lumber (SIC 24, 25)	2,171.35	14,796.71	Yes

Quarterly averages of total liquid assets and net worth of 1960, 1970, 1980, 1990, and 2000 for the fourteen sample industries covered by the Quarterly Financial Reports. All numbers are in 2000 dollars. Top three values by each indicator are marked by an asterisk. Industries are presented in the order of their rank in net worth. Data on the Quarterly Financial Reports are provided by the Census Bureau. Values for Lumber (SIC 24, 25) are the average of 1960, 1970, and 2000 only. See text for details.

ingly by Food, Health Care, and Transportation Equipment. We check the robustness of the results by estimating equation (2), excluding all the construction material industries. The results show the same pattern: the asymmetry in R&D's response appears stronger with the input-output IV and is the strongest with the idiosyncratic input-output IV, both by the bigger point estimates and by the smaller standard errors. Therefore, we interpret these results as R&D responding more strongly to industry-specific demand shocks, removing aggregate variations helps to isolate the components of input-output instruments mostly likely to possess good exogeneity and relevance properties, and therefore improving IV performance.

V. Liquidity Constraints

The estimated asymmetric responses of R&D and output to demand shocks, summarized in tables 3 and 5, are consistent with the opportunity cost hypothesis with 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 falls with output due to decreases in firms' net worth and therefore tighter liquidity constraints. This points to liquidity constraint as a key driving force for procyclical R&D.

While consistent with Aghion et al. (2005), our results contradict Barlevy (2004), who argues that liquidity constraint is not an important factor in explaining the cyclicality of R&D based on his finding that R&D by less constrained firms appears even more procyclical. To draw a more direct comparison with Barlevy (2004), this section studies the link between sample industries' financial strength and their R&D cyclicality. In particular, we adopt Barlevy's strategy by identifying industries that are less constrained financially, while continuing our approach of examining the cyclicality of industrial R&D over industry-specific cycles.

A. *The Quarterly Financial Reports*

We investigate sample industries' financial strength according to the Quarterly Financial Report (QFR) published by the U.S. Census Bureau. The QFR presents the income statements and the balance sheets for major manufacturing industries at the two-digit and the combination of three-digit SIC level. Unfortunately, industry groups defined by QFR and those in our sample do not fully coincide: it covers fourteen of our twenty sample industries. These fourteen financially identified industries are presented in column 1 of table 6. Column 4 of table 6 shows that nine of them possess valid input-output instruments.

Before identifying less constrained industries, it is important to examine whether our key results carry over to this financially identified subsample because it constitutes only 70% of the full sample. Therefore, we reestimate equations (1) and (2) for this 14-industry subsample. Panel A of table 7 presents the results on the relationship between R&D and contemporaneous output. The results with one-year and two-year lags stay qualitatively similar and are available upon request.

Apparently the key result, the asymmetric response of R&D to demand shocks, carries over. The estimated responses of R&D to demand-driven increases in output are all negative and significant at 10%, and those to demand-driven decreases in output are all positive, with only one of them statistically insignificant. Moreover, as the point estimates suggest, the asymmetry appears stronger with the input-output instruments and is the strongest with the idiosyncratic input-output instruments. According to the F-tests, one can reject $\beta_1 = \beta_2$ for all four IV estimations. In summary, panel A of table 7 suggests that the asymmetric response of R&D to demand shocks, consistent with the opportunity cost hypothesis with liquidity constraints, is present for the fourteen-industry subsample as it is for the twenty-industry full sample.

TABLE 7.—LIQUIDITY CONSTRAINTS

	Equation (1)	Equation (2)			
	Y	YD^H	YD^L	F-test $\beta_1 = \beta_2$	Observations
A: Financially Identified Industries (14 industries)					
OLS	0.0738	0.0492	0.0926	0.08	558
	(0.0750)	(0.1422)	(0.0734)	($p = 0.7877$)	
Real GDP IV	0.0790	−0.8515*	0.5173*	4.25	558
	(0.0866)	(0.4384)	(0.2523)	($p = 0.0599$)	
Industrial production IV	0.0364	−0.8492*	0.4759*	4.19	558
	(0.0753)	(0.4257)	(0.2441)	($p = 0.0613$)	
Input-output IV	−0.0221	−1.3871*	0.5828	3.85	358
	(0.1098)	(0.7191)	(0.3303)	(p=0.0854)	
Idiosyncratic input-output IV	−0.1762	−2.3335*	0.7423*	4.39	358
	(0.1405)	(1.1953)	(0.3918)	(p= 0.0694)	
B: Less Constrained Industries by Liquid Assets and by Net Worth: Food (SIC 20, 21), Petroleum Refining (SIC 29), and Machinery (SIC 35)					
OLS	0.0016	0.1424	−0.1337	1.49	120
	(0.0752)	(0.1690)	(0.1011)	($p = 0.2252$)	
Real GDP IV	0.1509	−1.9791	1.3500	0.28	120
	(0.1702)	(4.0448)	(2.2677)	($p = 0.5948$)	
Industrial production IV	0.1015	−3.4905	2.3566	0.19	120
	(0.1442)	(8.2609)	(5.3312)	(0.6662)	
Input-output IV	−0.2562*	0.0669	−0.5744	1.31	40
	(0.1332)	(0.3148)	(0.3738)	($p = 0.2602$)	
Idiosyncratic input-output IV	−0.3263**	−0.2779	−0.3616*	0.05	40
	(0.1581)	(0.3044)	(0.1882)	($p = 0.8260$)	

OLS and IV estimates of the relationship between R&D and output from 1958 to 1998 for fourteen financially identified industries and for the three industries less likely to be constrained financially. Standard errors reported in parentheses are controlled for within-industry heteroskedasticity and within-industry arbitrary serial correlation in panel A, and controlled for heteroskedasticity only in panel B. See text and notes to tables 2, 3, and 5 for more details on modeling specifications. See tables 4 and 6 for sample industries and their input-output instruments. See text for details.

Following Barlevy (2004), we proceed to examine two financial indicators: liquid assets (cash and U.S. government securities), which mitigate an industry's need to borrow externally, and net worth, which can be used as collateral for borrowing. The quarterly average of each indicator in 1960, 1970, 1980, 1990, and 2000 is calculated to assess the industries' financial strength over the entire 1958–1998 sample period.[11] Their values for the fourteen industries are presented in columns 2 and 3 of table 6, in the order of the industry's rank in net worth. As it turns out, Food (SIC 20, 21), Petroleum Refining (SIC 29), and Machinery (SIC 35) stand out as the top three by both indicators. Each reports quarterly average value, in 2000 dollars, of liquid assets of at least $10 billion and that of net worth of at least $100 billion. Moreover, their values of liquid assets and net worth well surpass all other industries. Food, financially the weakest among the three, reports 83% more liquid assets than Metal Products (SIC 34), the next highest by liquid assets, and 60% more net worth than Industry Chemicals (SIC 281–282, 286), the next highest by net worth. The rest of the eleven industries stay much closer in their values of liquid asset and net worth.

[11] For 1980 and 1990, Lumber (SIC 23, 24) was included in the category of "other durable manufacturing." Therefore, the listed values for Lumber in table 6 are the quarterly average of 1960, 1970, and 2000 only. We also tried interpolating the missing values for Lumber in 1980 and 1990 using the average 10-year growth rate from 1960 to 2000, which generates very similar value.

Therefore, we identify Food, Petroleum Refining, and Machinery as industries that are relatively less constrained financially. Unfortunately, column 4 of table 6 shows that only one of them, Petroleum Refining, possesses a valid input-output instrument. In fact, in table 6, industries with valid input-output instruments tend to be ranked low in financial strength. This should not be surprising: smaller industries usually possess less liquid assets and lower net worth, but it is also easier for smaller industries to satisfy the exogeneity criterion in finding valid input-output instruments because they constitute smaller cost shares of their downstream industries (Shea, 1993b).

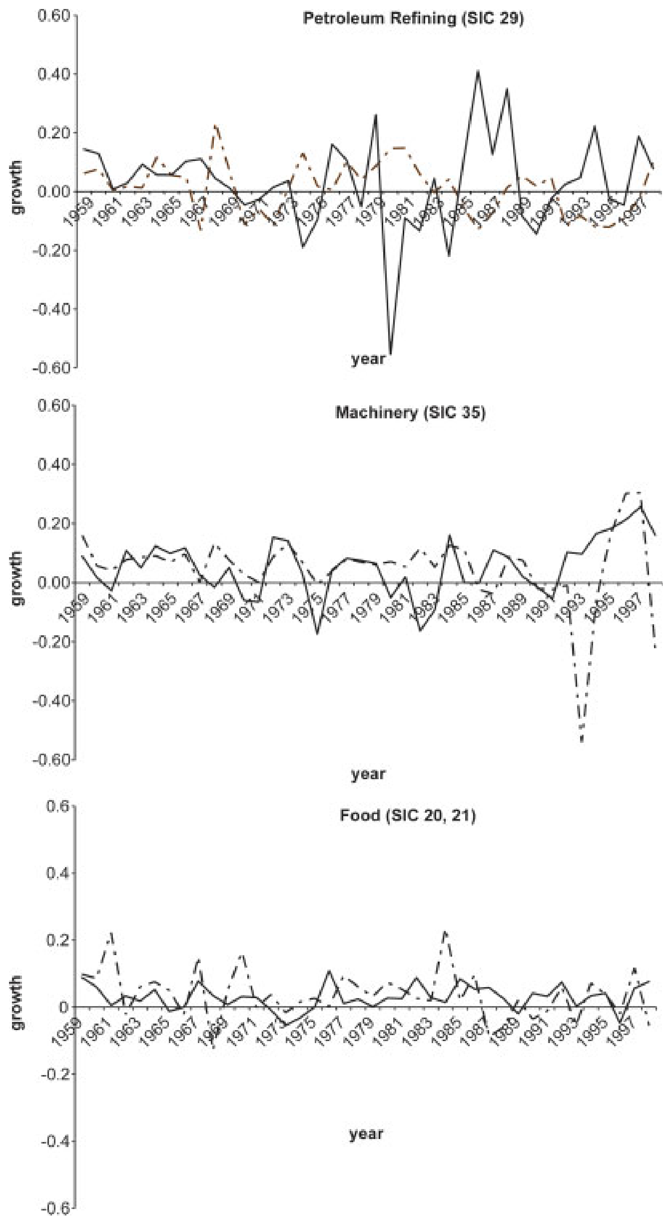
B. *The Cyclicality of R&D by Less Constrained Industries*

We examine the cyclicality of R&D for less constrained industries by estimating (1) and (2) for Food, Petroleum Refining, and Machinery. Two results are expected under the null of liquidity constraint. First, the asymmetric responses of R&D to demand shocks, which suggests the impact of liquidity constraints, should disappear for these three less constrained industries. Second, their R&D should respond negatively to demand shocks according to the opportunity cost hypothesis.

Panel B of table 7 summarizes the results. Standard errors controlled for heteroskedasticity are reported in parentheses. Column 2 presents the results from estimating equation (1). The OLS estimates and the aggregate-demand IV estimates are all positive but statistically insignificant.

Interestingly, the input-output IV estimates, which are supposed to outperform the aggregate-demand IV estimates, show that R&D responds negatively to demand-driven output fluctuations. In particular, corresponding to a 10% demand-driven output change, R&D moves in the opposite direction by 2.56% with raw input-output instruments, significant at the 10% level, and by 3.26% with idiosyncratic input-output instruments, significant at the 5% level. This contrasts sharply with the results from estimating equation (1) for the fourteen-industry subsample in panel A and those for the full twenty-industry sample shown in table 5. Columns 3 and 4 summarize the estimated output coefficients in equation (2): none is statistically significant. In Column 5, the *F*-tests suggest that one cannot reject $\beta_1 = \beta_2$ for all four IV estimations. Hence, the asymmetric response of R&D to demand shocks does not hold well for the three less constrained industries.[12]

FIGURE 1.—TIME-SERIES PLOTS OF GROWTH IN REAL R&D EXPENDITURES AND GROWTH IN OUTPUT



Solid line denotes output series; dashed line denotes R&D series. See notes to table 1 for variable definitions and data sources.

C. Discussion

We remain cautious in concluding from the results reported in table 7. For example, how should we interpret the statistically insignificant estimates in columns 3 and 4 of panel B? Does R&D by less constrained industries no longer respond asymmetrically to demand shocks? Or is the sample too small to detect an existing asymmetry? Moreover, the results with input-output instruments are based on forty observations only by Petroleum Refining as the only industry with a valid input-output instrument. But the aggregate-demand IVs produce insignificant estimates for the three less constrained industries altogether. This raises the question of how representative our results are.

We therefore take a more direct look at their R&D's cyclicality, presenting in figure 1 the time series of their R&D growth and output growth from 1958 to 1998. Figure 1 shows that R&D by Petroleum Refining is indeed counter cyclical: it moves in the opposite direction with output. However, R&D by Machinery co-moves positively with output except in the early 1980s; R&D by Food co-moves with output positively sometimes and negatively some other times. The 1958–1998 time-series correlations between R&D growth and output growth are -0.3144 for Petroleum Refining, 0.1627 for Machinery, and 0.0741 for Food. The differences in R&D's cyclicality of these three industries do not favor the liquidity constraint hypothesis because all three have been identified as less likely to be constrained financially.

Here are some possible explanations. First, note that table 6 suggests distinguished financial strength for Petroleum Refining; although it is ranked behind Machinery by liquid assets, it owns the highest net worth value—38.8% higher than that of Machinery. Thus, it is possible that net worth is the key factor in determining the binding of liquidity constraint and Petroleum Refining is the only industry passing that nonbinding criterion. Unfortunately, this explanation is difficult to verify because it is never clear theoretically or empirically what the appropriate conditions are for constraint not to bind.

Second, it is possible that R&D by Machinery and Food does respond negatively to demand shocks but appears procyclical due to some supply shocks that drive output and

[12] We also examined two alternative financial indicators: the ratio of liquid assets over total assets and the ratio of net worth over total assets. The top three industries by the liquid-asset ratio are Food, Petroleum Refining, and Ferrous Metals and those by the net-worth ratio are Drugs, Petroleum Refining, and Machinery. Estimating R&D's responses to demand shocks produces results similar to those reported in table 7. All results are available on request.

TABLE 8.—INDUSTRY-SPECIFIC CYCLE VERSUS AGGREGATE CYCLE: FOOD, PETROLEUM REFINING, AND MACHINERY—EQUATION(1)

	Industry-Specific Cycle		Aggregate Cycle		
	Y=Industrial Output Growth	R^2	*Y=Real GDP Growth*	R^2	*Observations*
Food (SIC 20, 21)	0.0269 (0.3124)	0.1563	−0.1210 (0.6798)	0.1573	40
Petroleum Refining (SIC 29)	−0.1264** (0.0525)	0.4310	−0.0592 (0.5341)	0.3818	40
Machinery (SIC 35)	0.5022** (0.2036)	0.2101	1.1158* (0.5795)	0.1537	40
Aggregated Sample	0.5116 (0.3058)	0.2042	0.7889* (0.4665)	0.1829	40
Pooled Sample	0.0016 (0.0752)	0.1437	0.3118 (0.3257)	0.1477	120

OLS estimates of R&D's cyclicality for Food, Petroleum Refining, and Machinery over their industry-specific cycles, indicated as industrial output growth, and over the aggregate cycle, indicated as real GDP growth. Rows 1–3 present estimation results for each of the industries separately. Row 4 presents estimation results using the aggregated sample with the total R&D and total output of the three industries. Row 5 presents results by pooling the three industries together. Robust standard errors controlled for heteroskedasticity are reported in parentheses. All estimations are conducted in growth rates. See text and notes to table 2 for modeling specifications; see text for details.

R&D to co-move positively. If those supply shocks share a common component across industries, they would be reflected in the aggregate fluctuations so that their impact cannot be isolated using the aggregate-demand IVs. This can explain why the aggregate-demand IVs produce insignificant estimates for three industries as a group in panel B of table 7.

D. Comparison with Previous Studies

Our results in table 7 contradict Barlevy (2004), for potentially two reasons. First, Barlevy examines firm-level financial strength, while we study industrial balance sheets. Second, Barlevy investigates the cyclicality of total R&D by less constrained firms over the aggregate cycle, while we explore the cyclicality of R&D by less constrained industries over their industry-specific cycles. Since the industry-specific cycles are not perfectly synchronized with the aggregate cycle, an industry's R&D may be countercyclical over its own cycle but appears procyclical over the aggregate cycle.

To assess this possibility, we perform two OLS estimations of equation (1). Y is measured as industrial output growth in the first estimation to indicate the industry-specific cycle and as real GDP growth in the second estimation to capture the aggregate cycle. The results are summarized in table 8. R&D by Food displays no significant correlation with either its own output or with aggregate output. R&D by Petroleum Refining is countercyclical over its own cycle, with a significant estimate of −0.1263 on Petroleum Refining output; however, such countercyclicality is weakened over the aggregate cycle, with an insignificant estimate of only −0.0592 on real GDP growth. For Machinery, R&D is procyclical over its own cycle, with a significant estimate of 0.5022 on Machinery output; the procyclicality is amplified over the aggregate cycle, as the estimate on real GDP growth stays significantly positive with a point estimate more than twice that on Machinery output. The bottom two rows of table 8 present the results from the aggregated and the pooled samples. Neither of the estimates on industrial output is statistically significant; the two estimates on real GDP growth, however, stay positive and are much larger in point estimate, with one of them significant at the 10% level.

Table 8 suggests that the cyclicality of industrial R&D over the industry-specific cycles indeed differs from that over the aggregate cycle. In general, the aggregate cycle tends to amplify R&D's procyclicality but weakens its countercyclicality.

VI. Conclusion

This paper investigates the opportunity cost hypothesis regarding the cyclicality of R&D using a panel of twenty U.S. manufacturing industries covering 1958 through 1998. The results confirm that R&D is procyclical. They also provide insights on the causes and the consequences of procyclical R&D. In particular, the IV estimations show that R&D declines always in response to demand fluctuations. We propose that liquidity constraint is an important factor in explaining the cyclicality of R&D, and support our findings with evidence on the link between industrial R&D cyclicality and financial strength.

It is important to point out that our results do not imply that R&D never increases, because they capture only R&D's response to demand shocks. Since R&D still appears procyclical at the industry level, there must be some other shocks that cause R&D to rise with output. For example, the arrival of new ideas and new technology can boost productivity and raise the return to innovation by helping a given level of R&D to generate more ideas and technologies, so that R&D and output increase together. Moreover, according to Griliches (1990), the bulk of R&D spending is spent on development; the arrival of new technology can also drive firms to perform more R&D for the purpose of developing the new technology into further productivity gains. Therefore, technology shocks are likely another important factor that causes procyclical R&D.

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 to explore the combined impact of liquidity constraints, demand shocks, and technology shocks on the cyclicality of R&D.

REFERENCES

Aghion, Philippe, George-Marios Angeletos, Abhijit Banerjee, and Kalina Manova, "Volatility and Growth: Credit Constraints and Productivity-Enhancing Investment," NBER working paper 11349 (2005).

Aghion, Philippe, and Gilles Saint-Paul, "Virtues of Bad Times: Interaction between Productivity Growth and Economic Fluctuations," *Macroeconomic Dynamics* 2:3 (1998), 322–344.

Alexopoulos, Michelle, "Read All about It: What Happens Following a Technology Shock," Department of Economics, University of Toronto working paper (2006).

Barlevy, Gadi, "On the Timing of Innovation in Stochastic Schumpeterian Growth Models," NBER working paper 10741 (2004).

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

Bartelsman, Eric, and Wayne Gray, "The NBER Manufacturing Productivity Database," NBER technical working paper 205 (1996).

Basu, Susanto, John Fernald, and Miles Kimball, "Are Technology Improvements Contractionary?" *American Economic Review* 96:5 (2006), 1418–1448.

Comin, Diego, and Mark Gertler, "Medium-Term Business Cycles," *American Economic Review* 96:3 (2006), 523–551.

Davis, Steven, and John Haltiwanger, "Job Creation, Job Destruction, and Job Reallocation over the Cycle," in Olivier Jean Blanchard and Stanley Fisher (Eds.), *NBER Macroeconomics Annual* (Cambridge, MA: MIT Press, 1990).

Eslava, Marcela, John Haltiwanger, Adriana Kugler, and Maurice Kugler, "The Effects of Structural Reforms on Productivity and Profitability Enhancing Reallocation: Evidence from Colombia," *Journal of Development Economics* 75:2 (2004), 333–371.

Fatas, Antonio, "Do Business Cycles Cast Long Shadows? Short-Run Persistence and Economic Growth," *Journal of Economic Growth Spring*, 5:2 (2000), 147–162.

Griliches, Zvi, "Patent Statistics as Economic Indicators: A Survey," *Journal of Economic Literature* 28:4 (1990), 1661–1707.

Hall, Robert, "Recessions as Reorganizations," in Olivier Jean Blanchard and Stanley Fisher (Eds.), *NBER Macroeconomics Annual* (Cambridge, MA: MIT Press, 1991).

Levin, Andrew, Chien-Fu Lin, and Chia-Shang James Chu, "Unit Root Tests in Panel Data: Asymptotic and Finite Sample Properties," *Journal of Econometrics* 108 (2002), 1–24.

Lucas, Robert E. Jr., *Models of Business Cycles* (Oxford: Basil Blackwell, 1987).

McConnell, Margaret, and Gabriel Perez-Quiros, "Output Fluctuations in the United States: What Has Changed since the Early 1980s?" *American Economic Review* 99:5 (2000), 1464–1476.

Ramey, Valerie, "Nonconvex Costs and the Behavior of Inventories," *Journal of Political Economy* 99:2 (1991), 306–334.

Schumpeter, Joseph, *Business Cycles: A Theoretical, Historical and Statistical Analysis of the Capitalist Process* (New York: McGraw-Hill, 1939).

Shea, John, "A Catalog of Demand-Shift Instrumental Variables for U.S. Manufacturing Industries," Department of Economics, University of Wisconsin at Madison (1990).

——— "Do Supply Curves Slope Up?" *Quarterly Journal of Economics* 108:1 (1993a), 1–32.

——— "The Input-output Approach to Instrument Selection," *Journal of Business and Economic Statistics* 11:2 (1993b), 145–155.

——— "What Do Technology Shocks Do?" in Ben S. Bernanke and Julio J. Rotemberg (Eds.), *NBER Macroeconomics Annual* (Cambridge, MA: MIT Press, 1998).

Syverson, Chad, "Market Structure and Productivity: A Concrete Example" *Journal of Political Economy* 112:6 (2004), 1181–1222.

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