On the Cyclicality of R&D*

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Abstract

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 pro-cyclical. 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 pro-cyclical; but interestingly, estimates using demand-shift instruments suggest that it responds asymmetrically to demand shocks. We propose that liquidity constraint is a key driving force for the observed pro-cyclicality of R&D.

Key words: R&D, growth, business cycles, demand shocks, liquidity constraint.
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1. 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 foregone 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 has repeatedly shown that one of the major sources of long-run growth – research and development – appears pro-cyclical. 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 such evidence, researchers have come to devise theoretical models to reconcile the opportunity-cost hypothesis with pro-cyclical 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 activities

[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.

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 significantly. If an industry's downturns happen to coincide with aggregate booms, then its R&D would appear pro-cyclical over the aggregate cycle dominated by other industries' activities. Therefore, pro-cyclical aggregate R&D may arise from an aggregation bias, rather than reflecting how producers balance production and innovation inter-temporally.

To reduce potential aggregation bias, we examine the cyclicality of R&D employing an annual panel of 20 U.S. manufacturing industries from 1958 to 1998. Our findings are as follows. On the one hand, R&D is in fact pro-cyclical at the industry level; industrial R&D commoves positively and significantly with industrial output. However, the disaggregate pro-cyclicality 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 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 from other supply shocks that can impact 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 that there is a potential positive impact of short-run downturns on long-run growth, but such a potential impact may be hindered by frictions such as liquidity constraint. We propose liquidity constraint is a key factor in explaining the pro-cyclicality of R&D, and further explore the impact of liquidity constraint on the cyclicality of R&D with data from industrial balance sheets.

The rest of this paper is organized as follows. Section 2 describes the data, and compares volatilities in R&D and output at the industry level with those at the aggregate level. Section 3 estimates industrial R&D's cyclicality over industry-specific cycles. The asymmetric response of R&D to demand shocks is examined in Section 4. Section 5 explores the liquidity-constraint hypothesis with data from industrial balance sheets. Section 6 concludes.

2. 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), compiled from the Industrial Survey of R&D (ISRD) conducted jointly by the NSF and Bureau of the Census. The NSF publishes R&D expenditures for 20 manufacturing industries from 1958 to 1998 at the two-digit and the combination of three-digit level of the1987 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 for the purpose of this paper. Some industry-year observations are suppressed to avoid

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

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 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 upon request.

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 database is compiled from the Annual Survey of Manufacturers (ASM) conducted by the Census. In the ASM, the Census tracks the identities of manufacturers using the Standard Statistical Establishment List, which is also used by the NSF as the sample frame for the ISRD. This suggests a good match between the MP data and the R&D data. Thus, we aggregate the MP data 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, 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 20 manufacturing industries covering 1958 through 1998.

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[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 and Wood (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 as it 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.

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).

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 real GDP growth in the U.S. averages 3% with a standard deviation of 2.2%; the annual growth in 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.

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 11.94%, and those of industrial output growth average 8.89%, both about four times as of 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 5.18% for Other Instruments (SIC 384-387); that of output growth ranges from 16.18% for Petroleum (SIC 29) to 3.61% for Drugs (SIC 283).

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). The vast differences in 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.

3. 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:

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

where i indicates industry, t indicates year, $B(L)$ is the lag polynomial operator, ε is the error term. $f(t)$ is a quadratic time trend: $f(t) = \left(t, t^2\right)$. We allow the slope of the time trend to differ before 1980 and afterward, as our R&D series display a jump in trend around 1980 for most of the sample industries. More specifically, $\lambda f(t) = \lambda_1 f(t) D_{it}^{pre80} + \lambda_2 f(t) D_{it}^{post80}$, where D_{it}^{pre80} is a pre-1980 dummy, D_{it}^{pre80} is a post-1980 dummy, and λ_1 and λ_2 are one-by-two vectors that capture the quadratic trend slopes before 1980 and afterward.[5] Starting from 1992, the NSF lowered significantly the size criterion in the ISRD. A post-1992 dummy, denoted as D^{92}, is included in (1) to capture any potential influence of this change in the process of data

[5] In all the regressions conducted in this paper, the estimated λ_2 stays statistically significant at 1% level. By contrast, imposing a common quadratic time trend throughout the sample period produces insignificant estimate on the trend and generate higher standard errors for other estimates. There are two possible explanations for the rise in R&D trend around 1980: it is likely related to a drop in aggregate volatility referred to as the Great Moderation; it is also likely related to a burst in innovation in 1980s encouraged by a rise in patent examiners at the U.S. Patent and Trademark Office.(McConnell and Perez-Quiros, 2000; Griliches, 1990)

collection. Taking off the post-1992 dummy produces quantitatively similar results but higher standard errors.

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.[6] While these partial correlations, in principle, may vary across industries, the common-slope coefficients on current and lagged output are imposed when estimating (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, or letting the post-1992 dummy to interact with the output coefficient. [7] 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.

3.1 Procyclical Industrial R&D

Table 2 summarizes results from OLS regressions of (1) with lag lengths of zero, one year, and two years. Standard errors accounting for within-industry heteroskedasticity and within-industry arbitrary serial correlation are reported in parentheses. The results confirm, from the disaggregated industry-level data, that R&D is *not* concentrated when production is low. The estimated relationship between R&D and contemporaneous output, as Column 1

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

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 Column 2 and Column 3, with lagged effects considered, a 10% increase in output is associated with a contemporaneous increase in R&D of 1.22%, 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 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, 2007), Comin and Gertler (2005), and Walde and Woitek (2004), who find that aggregate R&D appears pro-cyclical for both the U.S. and for G7 countries. However, Table 2 shows that the estimated pro-cyclicality of R&D at the industry level is much *milder* than that at the aggregate level. For example, Barlevy (2007) estimates the partial correlation between real GDP growth and aggregate R&D growth to be 0.69. In Table 2, the estimated partial correlation between industrial output growth and industrial R&D growth is 0.1351, only one fifth of the estimate by Barlevy (2007).

3.2. Can Liquidity Constraints Help the Opportunity-cost Hypothesis?

One explanation of why R&D is not concentrated when production is low focuses on the credit-market imperfections (Barlevy, 2007; 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.

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, here 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 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.[8]

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

The results, presented in last two columns 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

[8] 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.

close (around 0.13). Therefore, the opportunity-cost hypothesis fails the data again, even with the help of the liquidity constraints.

4. 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 (Saint-Paul, 1993). 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 that are consistent with the opportunity-cost hypothesis.

4.1 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, 1993) use aggregate output as demand-shift instruments for disaggregate 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 (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 estimations treat output as endogenous and employ current value and at least one lead of the aggregate-demand instruments for each output term. We employ the 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). We do not employ instrument lags and set the maximum instrument lead length at one year, because experimentations of various specifications show that the first-stage estimated coefficients on instrument lags and on instrument leads of two years or more are usually statistically insignificant. Nonetheless, changing the maximum instrument lead length or including additional instrument lags produces quantitatively similar results but higher second-stage standard errors. The IV estimates of the coefficients on output in (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 (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 (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 also 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 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 $\beta_1 = \beta_2$.

4.2 Input-output Instruments

The IV estimations employing aggregate-demand instruments detect asymmetric response of R&D to demand shocks that OLS cannot uncover. 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 impact industrial R&D directly, or if industry supply shocks have aggregate impacts through inter-industry linkages.

An alternative input-output approach is proposed by Shea (1993a, 1993b) that selects demand-shift instrument by examining inter-industry factor demand linkages (Syverson, 2004; Eslava et. al., 2004). According to Shea (1993b), the output of a down-stream industry *A* is considered a good instrument for an up-stream 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. 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, take 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 down-stream industries demand enough of their output to be truly relevant. Some other industries, like Autos and Others (371, 373-75, 379), comprise significant cost shares of all of their demanders, so that none of the down-stream industries' output can be really exogenous. Based on Shea (1990), we carefully examine the sources of demand and cost for each of our sample industries, and find that 10 of them possess reasonably good input-output instruments. These 10 industries, together with their input-output instruments and cost-demand relationships, are listed in Table 4; instruments data sources are described in 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 more than double of the share of the instrument industry's production cost (cost share) comprised by the two-digit sector containing the industry. The first criterion ensures instrument relevance, while the second promotes exogeneity through a high ratio of instrument relevance (demand share) to endogeneity (cost share). The cost share of the entire two-digit sector is examined to incorporate the possibility that industry supply shocks are strongly correlated within sector.

While input-output instruments are supposed to outperform aggregate-demand instruments in principle, they would be less useful if the comovement 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 from projecting the input-output instruments on the growth in real GDP and the growth in industrial production index.

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[9] 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). We also experimented with measuring the non-manufacturing output as growth in chain-weighted quantity measures published by the BEA. However, the corresponding results indicate substantial decrease in the first-stage F-statistics and substantial increase in the second-stage standard errors. We also explored using data on Construction Put in Place published by the Census to measure total construction when employed as IV; unfortunately, the series of Construction Put in Place starts at 1964, which would significantly truncate our R&D panel.

Accordingly, (1) and (2) are 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 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 down-stream demand shocks. We set the lead length at four years, as the first-stage estimated coefficient on the instrument lead of four years is statistically significant at 1% level for output decreases. Changing the maximum lead length or including additional instrument lags produces similar estimates but higher second-stage standard errors.

The results are summarized in Table 5. Panel A presents the results applying raw input-output instrument; Panel B presents those employing idiosyncratic input-output instrument. The IV estimates of (1), 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, some others are negative; but none are statistically significant. However, it is the estimates of (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 down-stream demand shock that *reduces* output by 10%, R&D declines by 4.77%; in response to a down-stream demand shock that *raises* output by 10%, R&D declines again by 11.85%. In Panel B when aggregate variations are removed from the instrument, 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 6.66%; 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 10 industries, are significant at 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 10 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 how representative our results are. Nonetheless, it is difficult to argue theoretically why construction material industries should feature stronger R&D elasticity. Moreover, our 10-industry sample also contains non-construction-related industries such as Paper (SIC 26), Drugs (SIC 283), and Rubber (SIC 37), instrumented correspondingly by Food, Health Care, and Transportation. We check the robustness of the results by estimating (2) with all the construction material industries excluded. The results show the same pattern: the asymmetry in R&D's response appears the strongest with the idiosyncratic input-output industries, both by the bigger point estimates and by the smaller standard errors. Therefore, we interpret these results as that R&D responds more strongly to industry-specific demand shocks, and that removing aggregate variations helps to isolate the components of input-output instruments mostly likely to possess good exogeneity and relevance properties, therefore improve the IV performance.

5. Liquidity Constraints

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

[10] As a further robustness check, we estimate (2) in two-year growths of R&D and output, employing two-year growth in demand instruments, at the purpose of incorporating 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 upon request.

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 pro-cyclical R&D.

While consistent with Aghion et. al. (2005, 2007), our results contradict Barlevy (2004), who argues liquidity constraint is not an important factor in explaining R&D's cyclicality, 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's cyclicality. In particular, we adopt Barlevy's strategy of identifying industries that are less constrained financially, while continue our approach of examining industrial R&D's cyclicality over their industry-specific cycles.

5.1. The Quarterly Financial Reports

We investigate sample industries' financial strength according to the Quarterly Financial Report (QFR) published by Bureau of the Census. 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 levels. Unfortunately, industry groups defined by QFR and those in our sample do not fully coincide: the QFR cover 14 of our 20 sample industries. These 14 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 re-estimate (1) and (2) for this 14-industry subsample. The results are summarized in Panel A of Table 7 on the relationship between R&D and contemporaneous output. The results with one-year and two-year lags are similar and 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 output increases are all negative and significant at 10%, and those to demand-driven output decreases are all positive, only one statistically insignificant. Moreover, as suggested by the point estimates, the asymmetry appears stronger with the raw input-output instrument, and is the strongest with the idiosyncratic input-output instrument. 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 R&D's asymmetric response to demand shocks, consistent with the opportunity-cost hypothesis with liquidity constraint, is present for the 14-industry subsample, as it is for the 20-industry full sample.

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 are calculated to assess the sample industries' financial strength over the entire 1958-1998 sample period.[11] Their values are presented in Columns 2-3 of Table 6, ranked by net-worth value. 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. They each report quarterly average value, in 2000 dollars, of liquid asset of

[11] For 1980 and 1990, Lumber (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 experimented with interpolating the 1980 and 1990 missing values for Lumber using the average 10- year growth in liquid asset or net worth from 1960 to 2000; the results from interpreted values are very close to those reported in Table 6.

at least $10 billion, and that of net worth of at least $100 billion. Moreover, their values of liquid asset and net worth *well surpass* those of 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 281-2, 286), the next highest by net worth. By contrast, the rest of the 11 industries stay much closer in the values of liquid asset and net worth.

Therefore, we identify Food, Petroleum Refining, and Machinery as industries that are less likely to be financially constrained. Unfortunately, Column 4 of Table 6 shows that only one of them – Petroleum Refining – possesses valid input-output instrument. As a matter of fact, industries with valid input-output instruments tend to rank low in Table 6 according to their financial strength. This is not surprising: it is small industries that usually possess less liquid assets and display lower net worth; but it is also smaller industries that are easier to find valid input-output instruments that satisfy the exogeneity criterion, as they constitute smaller cost shares of the down-stream industries (Shea, 1993).

5.2. 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 to be expected under the null of liquidity constraint. First, the asymmetric responses of R&D to demand shocks, which suggests the impact of liquidity constraint, should disappear. 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 (1). The OLS estimates and the aggregate-demand IV estimates are positive, but statistically insignificant. Interestingly, the IV estimates with the input-output instruments, which are supposed to outperform the aggregate-demand instruments, shows that R&D responds *negatively* to demand-driven output fluctuations. In particular, corresponding to a 10% demand-driven output change, R&D moves in *opposite* direction by 2.56% with raw input-output instrument, significant at 10% level, and by 3.26% with idiosyncratic input-output instrument, significant at 5% level. This contrasts sharply with the results in Panel A of Table 7 from estimating (1) for the 14-industry subsample and with those in Tables 3 and 5 for the 20-industry full sample. Columns 3-4 of Panel B summarize the results from estimating (2) for Food, Petroleum Refining, and Machinery: none is statistically significant. In Column 5 of Panel B, 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 seems not to hold well for the three industries that are less likely to be financially constrained.[12]

5.3. Discussion

We remain cautious in concluding from Table 7. For example, how should we interpret the statistically insignificant estimates summarized in Columns 3-4 of Panel B? Does R&D by the three less constrained industries no longer respond asymmetrically to demand shocks? Or is the sample not big enough to detect an existent asymmetry? Moreover, the results with input-output instruments are based on 40 observations only from Petroleum Refining, as the only less constrained industry with valid input-output instrument. But the aggregate-demand

[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 Furrous Metals (SIC 331-2, 3398-99); and those by the net-worth ratio are Drugs (SIC 283), Petroleum Refining, and Machinery. Estimating their R&D's responses to demand shocks produce results similar to those in Table 7. All results are available upon request.

IVs produce insignificant estimates for the three less constrained industries altogether. This raises the question how representative our results are.

We thus 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 opposite direction with output. However, R&D by Machinery appears procyclical: it commoves positively with output except for in the early 1980s; R&D by Food commoves with output positively sometimes and negatively some other times. The 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 Food, Petroleum Refining, and Machinery do not favor the liquidity-constraint hypothesis, because they have all been identified as financially less constrained industries.

Here are some possible explanations. First, Table 6 suggests distinguished financial strength for Petroleum Refining: while 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 whether liquidity constraint binds, and Petroleum Refining is the only industry passing that non-binding criterion.

Second, it is also possible that R&D by Machinery and Food do respond negatively to demand shocks, but appear pro-cyclical due to some supply shocks that drive output and R&D to commove positively. Those supply shocks, if sharing a common component across industries, would be reflected in aggregate fluctuations so that the aggregate-demand IVs cannot isolate R&D's response to demand shocks. This can explain why the aggregate-demand IVs produce insignificant estimates for the three industries together.

5.4. Comparison with Previous Studies

Our results in Table 7, once again, contradict Barlevy (2004). There are potentially two reasons for this contradiction. 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, it is possible that an industry's R&D is counter-cyclical over its own cycle, but appears pro-cyclical over the aggregate cycle. To assess this possibility, we perform two OLS estimations of (1). Y is measured as real GDP growth in the first estimation to capture aggregate cycle, and as industrial output growth in the second estimation to indicate industry-specific 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 counter-cyclical over its own cycle; such counter cyclicality of Petroleum R&D is *weakened* over the aggregate cycle, suggested both by lower absolute value of the point estimate and higher standard errors. For Machinery, R&D is pro-cyclical over its own cycle; the procyclicality of Machinery R&D is *amplified* over the aggregate cycle, with more than 100% increase in the point estimate. The bottom two rows present the results from the aggregated sample and the pooled sample: neither of the estimated coefficients on industrial output is statistically significant; however, those on aggregate output are both significant at 10% level as well as much bigger in point estimate.

In summary, Table 8 suggests that the cyclicality of R&D over the industry-specific cycle does differ from that over the aggregate cycle. In particular, aggregate cycle tends to amplify R&D's procyclicality but weakens its counter-cyclicality. This can explain why our results differ from those by Barlevy (2004).

7. Conclusion

This paper investigates the opportunity-cost hypothesis regarding the cyclicality of R&D, using a panel of 20 U.S. manufacturing industries covering 1958 through 1998. The results confirm that R&D is pro-cyclical. They also provide 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 liquidity constraint is an important factor in explaining R&D's cyclicality, and provide further evidence on the link between R&D's cyclicality and industrial financial strength.

It is important to point out that our results do not imply that R&D never increases, because they only capture 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 on the one hand, and raise the return to innovation on the other hand 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 drive firms to perform more R&D at the purpose of developing 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 exploring the combined impact of liquidity constraints, demand shocks, and technology shocks on the cyclicality of R&D.

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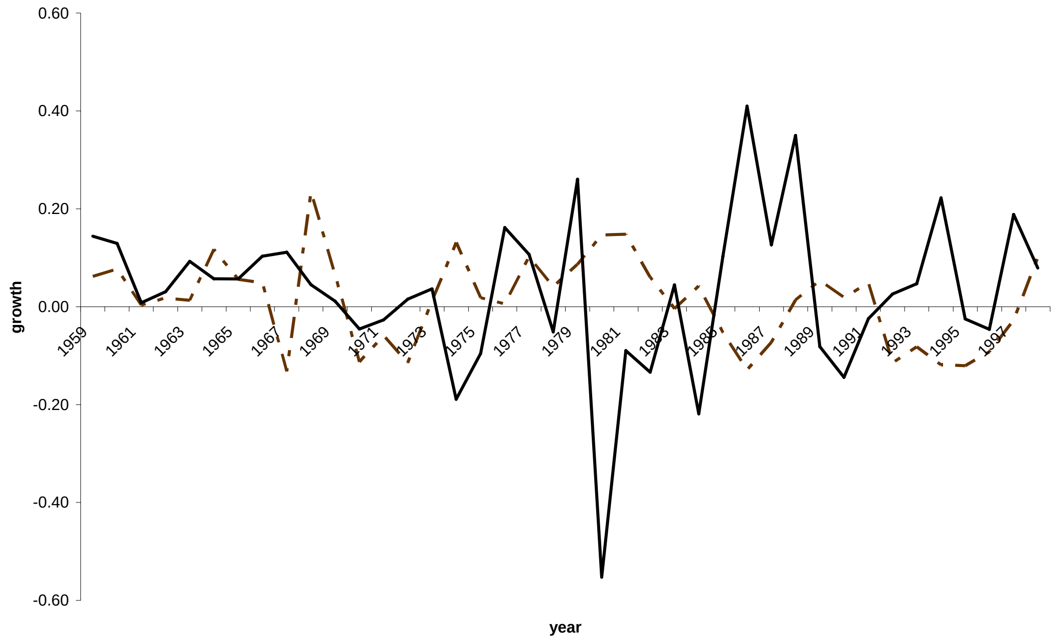
Figure 1

Panel 1: Petroleum Refining (SIC 29)



Panel 2: Machinery (SIC 35)

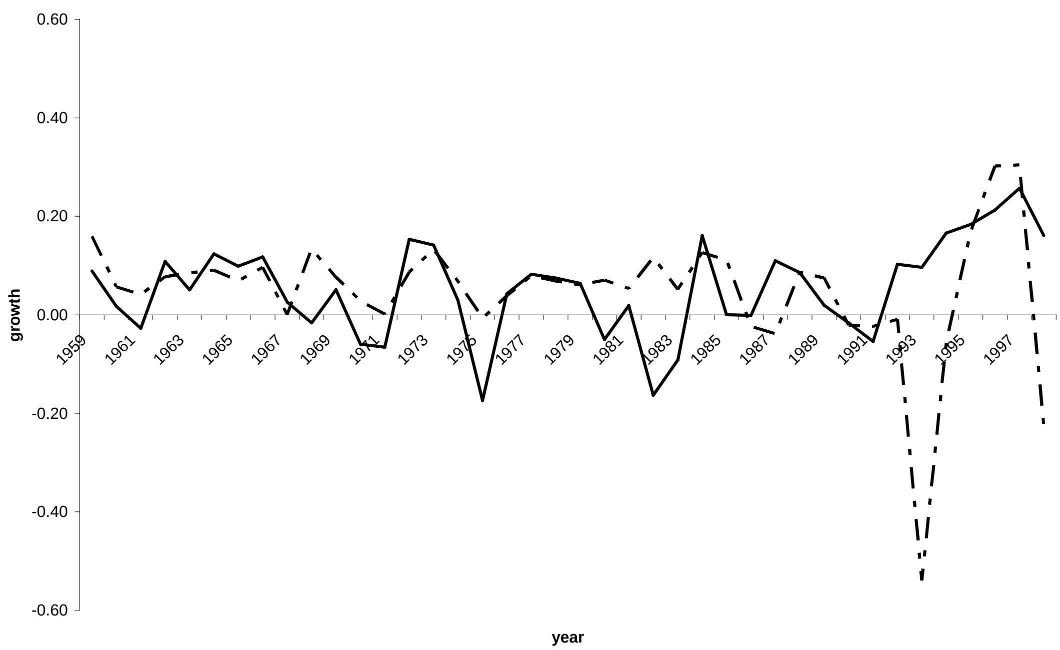
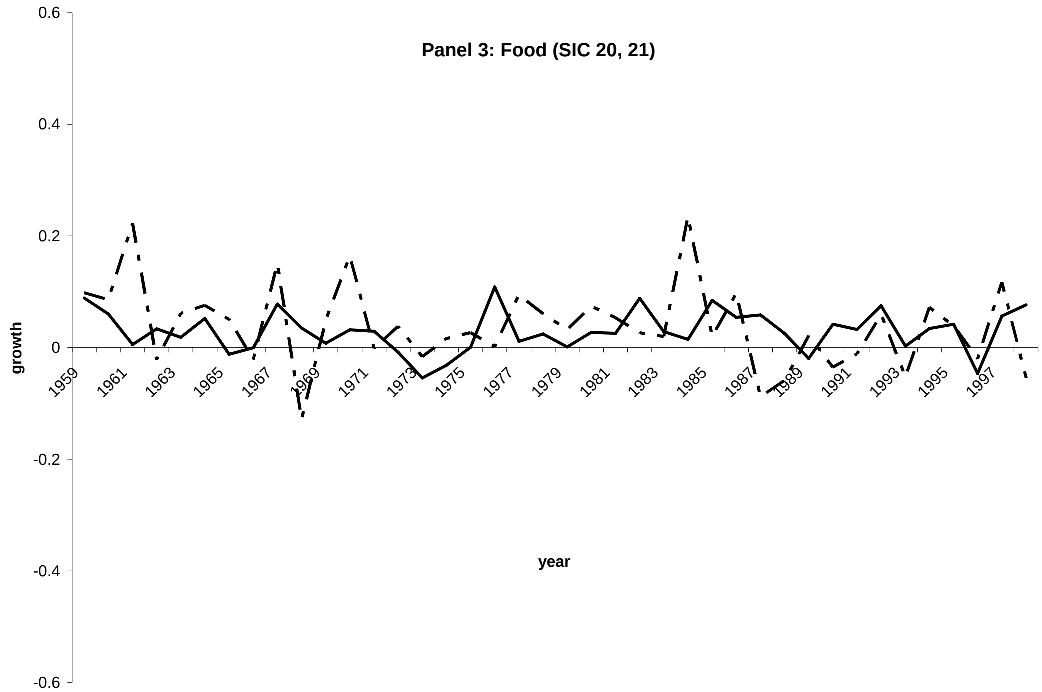


Figure 1 (Continued)



Notes: Time-series plots of growth in real R&D expenditure and growth in output by Petroleum Refining (SIC 29), Machinery (SIC 35), and Food (SIC 20, 21). Solid line denotes output series, dashed line denotes R&D series. See notes to Table 1 for variable definitions and data sources.

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

Industry	**Mean (R)**	**SD (R)**	**Mean (Y)**	**SD (Y)**
Food (SIC 20, 21)	3.88%	7.54%	2.96%	3.72%
Textiles (SIC 22m23)	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 281-2, 286)	2.83%	6.93%	3.18%	9.56%
Drugs (SIC 283)	7.63%	4.82%	5.22%	3.61%
Other chemicals (SIC 284-5, 287-9)	3.99%	12.19%	3.59%	5.21%
Petroleum (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 331-32, 3398-99)	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 Equip. (SIC 366-367)	7.05%	10.49%	11.02%	12.24%
Other Equip.(SIC 361-365, 369)	1.88%	12.77%	3.16%	7.39%
Autos and Others (SIC 371, 373-75, 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%**	**11.94%**	**3.64%**	**8.89%**
Aggregate Economy	**5.37%**	**3.42%**	**3.45%**	**2.12%**

Notes: 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 20 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.

Table 2: OLS

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

$$\text{OLS 2:}\quad R_{it} = \alpha + \beta_1 Y_{it} D_{it}^H + \beta_2 Y_{it} D_{it}^L + \lambda f(t) + \gamma D^{92} + \varepsilon_{it}$$

	OLS 1			**OLS 2**	
	Y	*Y*	*Y*	YD^H	YD^L
Contemp.	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 (0.0804)***	-	-
No. of obs.	794	774	754	355 for D^H=1	439 for D^L=1
F-test $\beta_1 = \beta_2$	-	-	-	0.04 (*p*=0.8532)	
R-squared	0.0364	0.0394	0.0411	0.0364	

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 corresponds to estimations of (1) with lag length of zero, one year, and two years. OLS 2 corresponds to estimation of (2) with 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 growth in year *t* is higher than its output growth 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

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

$$\text{IV 2:} \quad R_{it} = \alpha + \beta_1 Y_{it} D_{it}^{H} + \beta_2 Y_{it} D_{it}^{L} + \lambda f(t) + \gamma D^{92} + \varepsilon_{it}$$

	IV 1			**IV 2**	
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.	0.1540 (0.0804)*	0.1516 (0.0859)*	0.1688 (0.0878)*	-0.8659 (0.4433)*	0.6831 (0.2500)**
Cumulatively in one year	-	0.2425 (0.1170)*	0.2434 (0.1165)*	-	-
Cumulatively in two years	-	-	0.3108 (0.1286)**	-	-
F-test $\beta_1 = \beta_2$	-	-	-	5.42 (p=0.0311)	
Panel B: Industrial Production as IV					
	Y	Y	Y	YD^H	YD^L
Contemp.	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 (0.1239)**	-	-
F-test $\beta_1 = \beta_2$				5.77 (p=0.0267)	

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-square estimations treat output as endogenous and using real GDP and industrial production to instrument for industrial output. IV 1 corresponds to estimations of (1) with lag length of zero, one year, and two years. IV 2 corresponds to estimation of (2) with zero lag but allowing coefficient on out increases and output decreases to differ. Each IV regressions employ the current value and at least one-year lead of the instrument for each output term. See notes to Table 2 for more modeling 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 an up-stream industry's output share demanded by the corresponding down-stream industry, both directly and indirectly through other intermediate links; CS is a down-stream industry's cost share originating from the two-digit sector that contains the corresponding up-stream industry, both directly and indirectly through other intermediate links. Food (SIC 20, 21) 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 details.

Table 5: Input-output IVs

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

$$\text{IV 2:} \quad R_{it} = \alpha + \beta_1 Y_{it} D_{it}^{H} + \beta_2 Y_{it} D_{it}^{L} + \lambda f(t) + \gamma D^{92} + \varepsilon_{it}$$

	IV 1			IV 2	
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.	-0.0122 (0.1004)	-0.0619 (0.1196)	0.0047 (0.1089)	-1.1847 (0.6422)*	0.4767 (0.2428)*
Cumulatively in one year	-	0.0724 (0.1357)	0.0653 (0.1267)	-	-
Cumulatively in two years	-	-	0.2349 (0.2629)	-	-
F-test $\beta_1 = \beta_2$	-	-	-	3.85 (p=0.0814)	
Panel B: idiosyncratic input-output IV					
	Y	Y	Y	YD^H	YD^L
Contemp.	-0.1737 (0.1193)	-0.4181 (0.3055)	-0.6364 (0.5425)	-2.2899 (1.0674)*	0.6656 (0.3544)*
Cumulatively in one year	-	0.0479 (0.1487)	0.0839 (0.2231)	-	-
Cumulatively in two years	-	-	-0.3342 (0.4892)	-	-
F-test $\beta_1 = \beta_2$	-	-	-	4.99 (p=0.0524)	

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-square estimations treat output as endogenous and using raw and idiosyncratic input-output instruments to instrument for industrial output. Each regression employs current value and at least four instrument leads for each output term. All estimations are conducted in growth rates. See notes to Tables 2 and 3 for modeling specifications; see notes to Table 4 for sample industries and their input-output instruments; see text for more details.

Table 6: Industrial Financial Indicators and Input-output Instruments

Industries ranked by liquid Assets	Liquid Assets (million$)	Net Worth (million$)	Input-output Instruments
Petroleum (SIC 29)	*14754.12	*183509.58	Total construction
Machinery (SIC 35)	*16245.76	*132198.96	-
Food (SIC 20, 21)	*11745.77	*101281.77	-
Industry Chemicals (SIC 281-2, 286)	4386.66	63445.07	-
Metal Products (SIC 34)	6419.81	48729.80	-
Paper (SIC 26)	3330.01	48464.70	Food
Drugs (SIC 283)	5833.92	42115.68	Health Care
Furrous Metals (SIC 331-2, 3398-99)	6113.51	40692.58	Total construction
Other Chemicals (SIC 284-5, 287-9)	5602.33	40025.26	Agriculture
Non-Ferrous Metals (SIC 333-336)	2684.52	33835.19	Total Construction
Aerospace (SIC 372, 376)	4790.98	33411.20	-
Stones (SIC 32)	3611.92	31138.11	Total Construction
Rubber (SIC 30)	2482.09	24718.18	Transportation
Lumber (SIC 24, 25)	2171.35	14796.71	Total Construction

Notes: industries covered by the Quarterly Financial Reports (QFR), their values of liquid assets and net worth in 2000 dollars, and their input-output instruments. The listed industries are presented in the order of their ranks in net worth. A “*” indicates that the industry is among the top three by the corresponding financial indicator. A “-” indicates that the industry does not possess valid input-output instrument. The liquid-asset and net-worth values are the quarterly averages of 1960, 1970, 1980, 1990, and 2000; those for Lumber (SIC 24, 25) are the average of 1960, 1970, and 2000 only. The QFR are provided by Bureau of the Census. See Table 4 for the selection of input-output-instruments. See text for more details.

Table 7: Liquidity Constraints

$$(1): \quad R_{it} = \alpha + \beta Y_{it} + \lambda f(t) + \gamma D^{92} + \varepsilon_{it}$$

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

	(1)	**(2)**			**Obs.#**
	Y	YD^H	YD^L	F-test $\beta_1 = \beta_2$	
Panel A: Financially Identified Industries (14 industries)					
OLS	0.0738 (0.0750)	0.0491 (0.1422)	0.0926 (0.0734)	0.08 (*p*= 0.7877)	558
Real-GDP IV	0.0790 (0.0865)	-0.8514* (0.4384)	0.5172* (0.2522)	4.25 (*p*=0.0599)	558
Industrial-Production IV	0.0364 (0.0753)	-0.8491* (0.4256)	0.4758* (0.2440)	4.19 (*p*=0.0613)	558
Input-output IV	-0.0221 (0.1097)	-1.3870* (0.7190)	0.5827 (0.3302)	3.85 (*p*=0.0854)	358
Idiosyncratic input-output IV	-0.1761 (0.1404)	-2.3334* (1.1952)	0.7422* (0.3917)	4.39 (*p*= 0.0694)	358
Panel B: Less Constrained Industries by Liquid Wealth and by Net Worth: Food (SIC 20, 21), Petroleum Refining (SIC 29), and Machinery (SIC 35)					
OLS	0.0016 (0.0752)	0.1423 (0.1690)	-0.1337 (0.1011)	1.49 (p=0.2252)	120
Real-GDP IV	0.1509 (0.1701)	-1.9791 (4.0448)	1.3500 (2.2676)	0.28 (p=0.5948)	120
Industrial-Production IV	0.1015 (0.1442)	-3.4904 (8.2609)	2.3566 (5.3312)	0.19 (0.6662)	120
Input-output IV	-0.2562* (0.1332)	0.0668 (0.3148)	-0.5744 (0.3738)	1.31 (p=0.2602)	40
Idiosyncratic input-output IV	-0.3263** (0.1581)	-0.2779 (0.3044)	-0.3616* (0.1882)	0.05 (p=0.8260)	40

Notes: OLS and IV estimates of the relationship between R&D and output from 1958 to 1998 for the 14 financially identified industries and for the three industries less likely to be financially constrained according to Table 6. The two-stage least-square estimations treat output as endogenous and employ real GDP, industrial production index, raw and idiosyncratic input-output instruments to instrument for industrial output. In Panel B, only Petroleum Refining (SIC 29) possesses valid input-output instrument. The standard errors reported in parentheses in Panel A are controlled for within-industry heteroskedasticity and within-industry arbitrary serial correlation; those in Panel B are controlled for heteroskedasticity only. See notes to Tables 2, 3, and 5 for modeling specifications. See Table 6 for sample industries and their input-output instruments. See text for more details.

Table 8: Industry-specific Cycle v.s. Aggregate Cycle:
Food, Petroleum Refining, and Machinery

OLS 1: $R_{it} = \alpha + \beta Y_{it} + \lambda f(t) + \gamma D^{92} + \varepsilon_{it}$

	Industry-specific cycle		**Aggregate Cycle**		*No. of Obs.*
	Y=Industrial output growth	*R-sq*	*Y=Real GDP growth*	*R-sq*	
Food (SIC 20, 21)	0.0269 (0.3123)	0.1563	-0.1210 (0.6798)	0.1573	40
Petroleum Refining (SIC 29)	-0.1263** (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	0.3540* (0.1979)	0.0301	120

Notes: 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 aggregate cycle, indicated as real GDP growth,. The third, fourth, and fifth rows present estimation results for each of the industries separately. The sixth row presents estimation results from the aggregated sample, employing *total* R&D and *total* output of the three industries. The seventh row presents results by pooling the three industries together. Standard errors controlled for heteroskedasticity are reported in parentheses. All estimations are conducted in growth rates. See notes to Table 2 for model specifications; see text for more details.