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 constraints and technology improvement cause the observed pro-cyclicality of R&D.

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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 also been emphasized by other authors, including Davis and Haltiwanger (1990) and Hall (1991).

While some productivity-improving activities (such as reorganization and reallocation) are observed to be concentrated during recessions, aggregate data has repeatedly shown that one of the major sources of long-run growth – research and development – 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. Researchers have come to believe that such evidence contradicts the opportunity-cost hypothesis, and begin 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, examining an annual panel of R&D and output for 20 U.S.

[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.

manufacturing industries from 1958 to 1998. This provides far more observations on the relationship between R&D and output, 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, either because industry-level fluctuations are driven by industry-specific shocks, or because industries respond differently to common aggregate shocks. Suppose that aggregate R&D is dominated by a certain industry but real GDP is not, and suppose that this industry's downturns happen to coincide with aggregate booms. In that case, aggregate R&D would appear pro-cyclical, even though industrial R&D *is* in fact concentrated during industry-specific downturns. We call this an "aggregation bias", as it suggests that procyclical aggregate R&D may not necessarily contradict the opportunity-cost hypothesis.

To quantify such aggregation bias, we decompose the covariance between aggregate R&D and real GDP into a "within-industry" term, reflecting how different industries balance their output and R&D on average, and a "cross-industry" term, arising from the comovement between each industry's R&D with *other* industries' output. According to our approximation, the cross-industry term accounts for 86.64% of the observed covariance, implying that pro-cyclical aggregate R&D largely reflects the aggregation bias. To reduce such bias, we turn to our disaggregated industry panel to estimate the within-industry relationship between R&D and output.

Our results can be summarized 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. On the other hand, when demand-shift instruments are used to capture how disaggregated R&D respond to aggregate and industry-specific demand shocks, our 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, the estimated responses of R&D 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.[2] The asymmetric responses of R&D to demand shocks suggest that there is a *potential* positive impact of short-run downturns on long-run growth (as the negative response of R&D to positive demand shock suggests), but such a potential impact may be hindered by frictions such as liquidity constraints.

We propose that liquidity constraints and technology shocks are key factors in explaining the pro-cyclicality of R&D. Liquidity constraints prevent R&D from rising when output is low, while technology shocks cause R&D and output to increase together. We further explore our hypothesis using data on industrial balance sheets, on industrial TFP growth, and on patent applications.

The rest of this paper is organized as follows. Section 2 describes the data and examines the aggregation bias. Section 3 estimates the cyclicality of disaggregate R&D over industry-specific cycles. The IV approach is applied in Section 4. Section 5 explores the

[2] A recent study by Aghion et. al. (2007) finds a similar pattern employing firm-level data from France. R&D by more constrained firms falls during recessions, but do not increase proportionally during expansions.

liquidity-constraint hypothesis, studying industrial balance sheets. The impact of technology shocks on R&D's cyclicality is examined in Section 6. Section 7 concludes.

2. Pro-cyclical Aggregate R&D: within industry or cross industry?

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

$$R_t \cong \sum_{i=1}^{N} S_i^R R_{it} \ , \ Y_t \cong \sum_{i=1}^{N} S_i^Y Y_{it} \ ,$$

where S_i^R and S_i^Y are industry *i*'s long-run average share of aggregate R&D and that of aggregate output. Let S^R and S^Y denote 1-by-*N* vectors of long-run industry R&D shares and output shares, and let Ω^{RR}, Ω^{YY} and Ω^{RY} be the *N*-by-*N* variance-covariance matrixes of industrial R&D, of industrial output, and between industrial R&D and industrial output correspondingly. Then, the variance-covariance matrix of aggregate R&D growth and aggregate output growth is approximately

$$(1) \begin{pmatrix} S^R \Omega^{RR} S^{R\prime} & S^R \Omega^{RY} S^{Y\prime} \\ S^R \Omega^{RY} S^{Y\prime} & S^Y \Omega^{YY} S^{Y\prime} \end{pmatrix},$$

Each term in (1) can be further decomposed into a "within-industry" term from the diagonal elements of Ωs, as the average variance (or covariance) of each industry's own activities, and a "cross-industry" term from the off-diagonal elements of Ω, as the average *co-movement* between each industry's activities with *other* industries' activities. Apparently, it is the "within-industry" term of Ω^{RY} that reflects how different industries balance innovation and production on average, the "cross-industry" term of Ω^{RY} captures the aggregation bias that

may cause aggregate R&D procyclical, but that does not truly contradict the opportunity-cost hypothesis. In an extreme case, suppose that the diagonal elements of Ω^{RY} are all zeros, implying that each industry's R&D do not correlate with its output, but the off-diagonal elements sum up positive, suggesting that some industries' R&D commove positively with other industries' output, then aggregate R&D would appear pro-cyclical. But such pro-cyclicality is entirely driven by the aggregation bias.

An important note should be made. Industry definition should impact the relative size of cross-industry term and within-industry term in (1). Likely the magnitude of the cross-industry term rises when industries are defined at a more detailed level. In that sense, only a firm panel that covers the entire universe of the economy over a long time frame can best assess the potential aggregation bias. Nonetheless, we proceed with a disaggregated industry panel, as the first step in this literature to investigate the impact of such bias on the cyclicality of R&D.

2.1. Data

Two data sources are combined to construct a disaggregated industry panel of R&D and output. Data on R&D by industry is taken from the National Science Foundation (NSF), which publishes nominal R&D expenditures for 20 two-digit and three-and-a-half digit manufacturing industries based on the Standard Industry Classification (SIC) system from 1958 to 1998.[3] R&D by other industries is published under two raw categories of "other

[3] Starting from the 1999 NSF R&D survey, industries are defined under the North American Industry Classification System (NAICS). To made year-to-year comparison more convenient, the NSF transforms the 1997 and 1998 series originally under the SIC into those under the NAICS, but not the other way around. Therefore, constructing a panel beyond 1998 would require transforming the entire 1958-1998 industrial R&D series under SIC into ones under NAICS. We do not pursue in that direction because we worry such transformation may involve two many errors, as the NSF claims that "the estimates for 1997 and 1998 (after

manufacturing" and "non-manufacturing". We exclude these two R&D series from our panel because they cover too many unrelated industries, thus are inappropriate for our future strategy of examining R&D's cyclicality over industry-specific cycles.

While the NSF publishes both company-financed and federal-financed R&D, we use only data on company-financed R&D for the purpose of exploring the opportunity-cost hypothesis. Some industry-year observations are suppressed by the NSF 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), we use growth in total R&D to interpolate gaps in the series of company-financed R&D. Throughout the paper, "R&D" refers to company-financed R&D unless noted otherwise. Following Barlevy (2007), we convert the R&D series into 2000 dollars using the GDP deflator. Alternative deflators from the R&D Satellite account published by the Bureau of Economic Analysis (BEA) 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 data are aggregated to industries at the two-digit/three-and-a-half-digit level as defined in the R&D series. Output is measured as real value added, as the deflated value added using shipment-value-weighted price deflator.[4] Combining the R&D data

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transformation) are not necessarily representative of the NAICS categories of industries in those years." (http://www.nsf.gov/statistics/srs01410/).

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

and the MP data gives us an annual panel of R&D and output by 20 manufacturing industries from 1958 to 1998, accounting for 82.5% of aggregate R&D and 20.52% of real GDP over this sample period.

2.2 Decomposition Results

We apply our industry panel to (1) to decompose the variances and covariance of aggregate R&D growth and real GDP growth. However, our industry panel *alone* is not sufficient for this task, as it accounts for only a proportion of aggregate R&D and real GDP. Additional R&D series for "other manufacturing" and "non-manufacturing" are from the NSF. Additional output series for "other manufacturing" are compiled from the MP database; those for "non-manufacturing" are from the BEA. Accordingly, S^R and S^Y are 1-by-22 vectors of 1958-1998 average industry R&D shares and output shares. Ω^{RR}, Ω^{YY}, and Ω^{RY} are set equal to the observed 1958-1998 inter-industry variance-covariance matrixes of industrial R&D, of industrial output, and between industrial R&D and industrial output.

Table 1 presents our decomposition results. Column 1 summarizes the actual statistics from aggregate data; Column 2 displays the corresponding values approximated by (1); Columns 3 and 4 decompose the approximated values into "within-industry" terms and "cross-industry" terms. Apparently, a large amount of the variances and covariance of aggregate R&D growth and real GDP growth arises from cross-industry comovement. The cross-industry term accounts for 63.8% of volatilities in real GDP growth, and 23.36% of variances in aggregate R&D growth. Most importantly, it *dominates* the comovement between aggregate R&D growth and real GDP growth by taking 86.64% of their covariance. In particular, the actual 1958-1998 covariance between aggregate R&D growth and real GDP

growth is 0.0244%; the approximated covariance by (1) is 0.0251%, of which only 0.0034% is from the within-industry component, but 0.0218% is contributed by the cross-industry component.

Table 1 suggests that the observed pro-cyclical aggregate R&D is largely due to the *inter-industry* comovement of R&D and output. By contrast, the opportunity-cost hypothesis captures how producers balance production and innovation inter-temporally, so that carrying it to the data requires correlating industries' R&D with their own output. What drives such inter-industry comovement between R&D and output is on its own of research interest, but is beyond the scope of this paper. Thus, we turn to our industry panel to focus on the diagonals of Ωs – the within-industry volatilities of disaggregated R&D and output.

2.3. Disaggregated Volatilities

Table 2 summarizes the sample means and the sample standard deviations of industry-level R&D growth and output growth. Corresponding statistics for aggregate data are listed at the bottom row for comparison. Figure 1 presents the time-series plots for aggregate company-financed R&D growth and real GDP growth in Panel 1, and industrial R&D growth and industrial output growth in Panel 2 for one of our sample industries: Electronics and Communications Equipments (SIC 366-367).

Two messages can be taken away from Table 2 and Figure 1. First, R&D and output are much more volatile at disaggregated industry level: the standard deviations of industrial R&D growth average 11.94%, and those of industrial output growth average 8.89%, both 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); and the time-series correlations of industrial R&D growth with the aggregate company-financed R&D growth ranges from -0.3314 for Autos and Others (SIC 371, 373-75, 379) to 0.5108 for Aerospace (SIC 372,376).

The vast differences in these industries' time-series correlations with aggregate fluctuations, together with Table 2, confirms 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 Disaggregated Cyclicality of Disaggregated R&D

3.1 Model Specifications

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

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

where *i* indicates industry, *t* indicates year, *B(L)* is the lag polynomial operator, ε is the error term. The slope of a quadratic time trend, denoted as *f(t)*, is λ, which is allowed to differ

before 1980s and afterward to capture the burst in innovation since the 1980s. For surveys prior to 1992, the frame was limited to companies above certain size criteria based on number of employees. Starting from 1992, the size criteria were lowered considerably. A post-1992 dummy, denoted as D^{92}, is included to capture any potential influence of this change in the process of data collection.

When (2) is estimated using OLS, the estimates of *B(L)* represent the partial correlation between R&D growth and current or lagged output growth.[5] While these partial correlations, in principle, may vary across industries, the common-slope coefficients on current and lagged output are imposed when estimating (2) to obtain sufficient degrees of freedom due to the short time series of annual data. Experimentations with different specifications of the model suggest that our results are robust to taking off the quadratic time trend, imposing common slopes of the quadratic time trend, allowing industry-specific time trend, including industry fixed effects, 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. Results from regressions with lag lengths of zero, one year, and two years are summarized in Table 3. We set maximum output lag length 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 tends to be statistically insignificant. Standard errors accounting for within-industry heteroskedasticity and within-industry arbitrary serial correlation are reported in parentheses.

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

Table 3 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 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, Table 3 does not support the opportunity-cost hypothesis that R&D activities are concentrated when production is low. They are consistent with findings by Fatas (2000), Barlevy (2004), Comin and Gertler (2005), and Walde and Woitek (2004), who examine aggregate data and find that R&D appears pro-cyclical for both the U.S. and for G7 countries. Table 3 shows that the opportunity-cost hypothesis fails at the disaggregated level as well.

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

One explanation of R&D is not concentrated when production is low focuses on the credit-market imperfections (Barlevy, 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 (2007) tests the liquidity-constraint hypothesis by examining the cyclicality of R&D performed by companies with non-binding constraints, identified as the top 10% R&D-performing companies ranked by their liquid assets or net worth. 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 indicates the industry's representative firms' net worth, so that lower output implies tighter liquidity constraints, then the opportunity-cost hypothesis should only fail in one direction. When output declines, tighter liquidity constraints prevent R&D from increasing, so that R&D tracks the decline in output; but when output increases, R&D moves in opposite direction as the opportunity-cost hypothesis suggests. Put differently, under the opportunity-cost hypothesis with liquidity constraints, the response of R&D to output should be asymmetric.[6]

Accordingly, (3) 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; $D_{it}^{H} = 1 - D_{it}^{L}$.

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

The results, presented in the fourth column of Table 3, 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

[6] 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. In reality, there may be supply shocks that affect R&D directly, so that the observed cyclical properties of R&D are driven by a mix of demand and supply shocks. In principle, appropriate demand-shift instruments can isolate the output and R&D responses to demand shocks, to see whether such shocks generate results that are consistent with the opportunity-cost hypothesis.

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 (2) and (3) 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 for each output term and one lead of the instruments. We employ instrument lead because un-observable shocks to final demand may be first reflected as intermediate output

before they are reflected in measured final output (Shea, 1993a, Syverson, 2004).[7] The IV estimates of the coefficients on output in (2) and (3) reflect the response of R&D to output changes attributable to aggregate demand shocks approximated as aggregate output.

The results are summarized in Table 4. Panel A of Table 4 presents the results with real GDP growth as the demand-shift instrument. The IV estimates of (2), 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 (3), summarized in the fourth column, show that such positive responses mainly comes that R&D and output decline together in response to a negative demand shock that causes output to decline. More specifically, in response to a demand shock that causes output to decline by 10%, R&D declines again by 6.83%, significant at the 5% level. But, in response to a demand shock that *raises* output by 10%, R&D *declines* by 8.66%, significant at 10% level. Panel B of Table 4 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 results from the IV estimates employing aggregate-demand instruments are consistent with the opportunity-cost hypothesis with liquidity constraints. However, as argued earlier, aggregate output is not ideal demand-shift instruments. A good instrument is supposed to be relevant to output growth, but exogenous with R&D growth. Aggregate output is relevant yet not exogenous, especially if a large part of aggregate output fluctuations reflects

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

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 activities in Drugs if Health Care covers a large share of the demand for Drugs output, while Drugs, and 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 any down-stream industries' output cannot that 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 5; instruments data sources are described in notes to Table 5.[8] The input-output instruments for these 10 industries

[8] Empirical literature has argued that price changes in non-manufacturing sectors are poorly measured (Shea, 1998). Therefore, we use growth in sector employment to approximate non-manufacturing output following Shea (1993a). When we tried measuring non-manufacturing IVs as growth in chain-weighted quantity measures published by the BEA, the first-stage F-statistics decrease and the second-stage standard errors increase

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

Accordingly, (2) and (3) are estimated applying input-output instruments as well as their idiosyncratic components to the restricted sample of 10 industries listed in Table 5. The two-stage least-square estimations treat output as endogenous and employ current values of each output term as well as four leads of the raw or idiosyncratic input-output instruments.[9]

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substantially. We do not use the series of construction value put in place published by the Census to measure Construction because it starts from 1964 while our panel starts from 1958.

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

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.

The results are summarized in Table 6. Panel A presents the results employing raw input-output instruments; Panel B presents those with idiosyncratic input-output instruments. The IV estimates of (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, some others are negative; but none are statistically significant. However, it is the estimates of (3), 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 instruments, the asymmetric responses of R&D to demand-driven output changes become *stronger*: in response to a 10% idiosyncratic demand-driven decrease in output, R&D declines by 6.66%; 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 5 suggests that, for six out of the 10 industries, industrial output is instrumented by Total Construction output when applying the

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[10] As a further robustness check, we re-estimate (3) 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 upon request.

input-output IV approach. This implies a sample heavily weighted toward construction material industries, and raises the question how representative our results are. However, 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 (3) with all the construction material industries excluded. Consequently, the same pattern arises: 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 such 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, as summarized in Table 4 and Table 6, 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 declines with output due to decreases in firms' net worth and therefore tighter liquidity constraints. This suggests liquidity constraints as one of the key driving forces for pro-cyclical R&D.

While consistent with Aghion et. al. (2007), our results contrast Barlevy (2007), who finds that real R&D expenditure by less constrained firms appear even more pro-cyclical.

Barlevy therefore argues that liquidity constraint is not what drives R&D pro-cyclical, because those firms, while relatively free to concentrate their R&D during downturns, seem not to do so in reality. Barlevy's finding is based on his examination of the relationship between less constrained firms' R&D and *aggregate output* rather than these firms' own output. But output cyclicality by less constrained firms may not be perfectly synchronized with aggregate cycle. It is possible that firms by certain industries are financially stronger in general. If these industries' downturns usually coincide with the aggregate expansion, then their R&D expenditure may appear pro-cyclical with the aggregate cycle but are, in fact, concentrated during their industry-specific downturns – our disaggregate approach is designed to avoid such biases.

To draw a more direction comparison with Barlevy (2007), we adopt in this section Barlevy's strategy by identifying industries that are less constrained financially, while continue our approach of examining the cyclicality of industrial R&D over industry-specific cycles.

5.1. The Quarterly Financial Reports

We examine sample industries' financial strength according to the Quarterly Financial Report (QFR) published by the Census of 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 14 of our 20 sample industries. These 14 financially identified industries are presented in Column 1 of Table 7. Column 4 of Table 7 shows that nine of them posses 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 (2) and (3) for this 14-industry subsample. Panel 1 of Table 8 summarizes the results. Only the results of estimating (2) without output lags are presented, as those with lags stay qualitatively similar.

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 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 1 of Table 8 suggests that R&D's asymmetric response to demand shocks, which points to the impact of liquidity constraints, is present for the 14-industry subsample, as it is for the 20-industry full sample.

We then follow Barlevy (2007) by examining 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 industries' financial strength over the entire 1958-1998 sample period.[11] Their values for the 14 industries are presented in Columns 2-3, Table 6, in the order of industry's rank in net worth. As it turns out, Food (SIC 20, 21), Petroleum Refining (SIC 29), and Machinery (SIC

[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 also tried interpolating the missing values in 1980 and 1990 using the average 10- year growth rate from 1960 to 2000, which turned out very close to the reported value.

35) stand out as the top three by both indicators. They each report quarterly average value, in 2000 dollars, of liquid-asset of at least $10 billion, and that of net worth of at least $100 billion. Most importantly, their values of liquid asset 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 asset, and 60% more net worth than Industry Chemicals (SIC 281-2, 286), the next highest by net worth. By contrast, the rest 11 industries stay much closer in their values of liquid asset and net worth.

Therefore, we identify Food, Petroleum Refining, and Machinery as industries that are relatively less constrained financially. Unfortunately, Column 4 of Table 7 shows that only one of them – Petroleum Refining – possesses valid input-output instrument. As a matter of fact, in Table 7 industries with valid input-output instruments tend to be ranked low in their financial strength. This should not be surprising: industries that produce less tend to possess less liquid asset and lower net worth; but it is easier for them to satisfy the exogeneity criterion in finding valid input-output instruments, as they constitute smaller cost shares of their 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 (2) and (3) 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 constraints, should disappear. Second, their R&D should respond negatively to demand shocks as the opportunity cost hypothesis suggests.

Panel 2 of Table 8 summarizes the results. Standard errors reported in parentheses are controlled for heteroskedasticity. The estimated output coefficients in (3) are presented in

Columns 3-4: 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 seems not to hold well for theses three less constrained industries.

Column 2 presents the results from estimating (2). The OLS estimates and the IV estimates with aggregate-demand instruments are positive, but statistically insignificant. Interestingly, the IV estimates with input-output instruments, which are supposed to outperform 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 instruments, significant at 10%, and by 3.26% with idiosyncratic input-output instruments, significant at 5%. This contrasts sharply with the results from estimating (2) for the 14-industry subsample in Panel 1 and those with the full 20-industry sample shown in Tables 4 and 6, again consistent with the opportunity-cost hypothesis with liquidity constraints.

5.3. Discussions

We remain cautious in concluding from Table 8. For example, how should we interpret the statistically insignificant estimates in Columns 3 and 4 of Panel 2? Do R&D by these 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 from Petroleum Refining alone, as the only less constrained industry with valid input-output instrument. But aggregate-demand IVs produce insignificant estimates for the three less constrained industries altogether. This raises the question how representative our results are.

We therefore take a more direct look at their R&D's cyclicality, presenting in Figure 2 the time series of real R&D expenditure growth and output growth for Petroleum Refining in Panel 1, those for Machinery in Panel 2, and those for Food in Panel 3. The 1958-1998 time-series correlations between real R&D expenditure growth and output growth are -0.3144 for Petroleum Refining, 0.1627 for Machinery, and 0.0741 for Food.

Looking at the time series, R&D by Petroleum Refining is indeed counter-cyclical: it tends to move in opposite direction with output. This is consistent with the input-output IV estimates in Panel 2 of Table 8, implying that fluctuations in Petroleum Refining should actually be demand-driven. However, R&D by Machinery appears to commove positively with output (except for the early 1980s); R&D by Food commoves with output sometimes positively, some other times negatively. The differences in R&D's cyclicality among Petroleum Refining, Machinery, and Food do not favor the liquidity-constrained hypothesis, because all three have been identified as less likely to be constrained financially.

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. Moreover, Petroleum Refining is the only industry that remains among the top by both indicators, implying its superior financial strength. 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 the non-binding criterion. Unfortunately, this explanation is difficult to verify, because, as argued in Section 2, it is never clear theoretically or empirically what are the appropriate levels for the constraint not to bind.

Second, it is also possible that R&D by Machinery and Food do respond negatively to demand shocks; they appear pro-cyclical due to some supply shocks that drive output and R&D to commove positively. The aggregate-demand IVs cannot isolate R&D's response from the impact of these supply shocks, because such shocks are reflected in the aggregate fluctuations by sharing a common component across industries. This can explain why the real-GDP and IP IVs produce insignificant estimates for all three industries together in Panel 2 of Table 7. Verifying this explanation requires identifying what these supply shocks are, since Machinery and Food do not possess valid input-output IVs.

Third, we may have been using the wrong indicators. The high net-worth or liquid-asset value for the entire industry can rise from a size effect – as the sum of a large number of firms with low net worth or liquid asset. We therefore examine two alternative financial indicators: the *ratios* of net worth and liquid asset over the industry's total assets. As a result, Machinery loses its advantages by reporting the lowest liquid-asset ratio; Food moves to the bottom three by the net-worth ratio. But, Petroleum Refining once again remains among the top three by either ratio. The top three 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. Since either group includes *two* industries that possess valid input-output instrument: in addition to Petroleum Refining, Furrous Metals can be instrumented by Total Construction, and Drugs can be instrumented by Health Care. We therefore re-estimate (2) and (3) for each of the two groups as a further robustness check.

Our results are summarized in Table 9. Apparently, the results with input-output IVs stay quantitatively similar to those in Panel 2 of Table 8. R&D responds negatively to input-output demand shocks. Out of the four negative IV estimates, one is significant at 1% lYevel,

two significant at 5% level, and one at 10% level. This, once again, points to the possibility that liquidity constraint is a key force in driving the contradiction between R&D's cyclicality and the opportunity-cost hypothesis. [12]

5.4. Comparison with Previous Studies

Our results, once again, contrast Barlevy (2007). 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 *aggregate* cycle, while we explore the cyclicality of R&D by less constrained industries over their *industry-specific* cycles. As argued earlier, industry-specific cycles are not perfectly synchronized with aggregate cycle. Thus, it is possible that an industry's R&D is counter-cyclical over its own cycle, but appears pro-cyclical over aggregate cycle.

Table 10 assesses this possibility. We estimate (2) by OLS *twice* for Food, Petroleum Refining, and Machinery: Y is measured as industrial output growth to indicate industry-specific cycle in the first estimation, and as real GDP growth to capture aggregate cycle in the second estimation. The third, fourth, and fifth rows summarize the results from separate estimations for each of the three industries. For Food, R&D growth displays no significant partial correlation with either Food output growth or real GDP growth. For Petroleum Refining, R&D is counter-cyclicality over its own cycle: the estimated coefficient on Petroleum output growth is 0.1263, significant at 5% level. However, the estimated partial

[12]We report these results only as a robustness check, because both ratios have an important weakness as financial indicators: the values of the liquid-asset ratio and net-worth ratio by the 14 industries are in general quite close, so that the top three industries' advantages are very small. By contrast, the indicators of net worth or liquid asset are able to identify Food, Machinery, and Petroleum Refining as three industries with total values of net worth and liquid asset well above all other industries.

correlation between R&D growth by Petroleum Refining and real GDP growth is much smaller in absolute value, and statistically insignificant. For Machinery, R&D is pro-cyclical over its own cycle: the estimated coefficient on Machinery output is 0.5022, significant at 5% level. Such pro-cyclicality is *amplified* over aggregate cycle according to the point estimate: the estimated coefficient on real GDP growth is 1.1158 and significant at 10% level.

We then estimate (2) by OLS again, measuring R as growth in *total* real R&D expenditure by the three less constrained industries, and Y as real GDP growth. This is parallel to Barlevy's study of the relationship between real GDP growth and growth in total R&D by less constrained firms. Interestingly, our results, presented in Column 4 of the sixth row, suggest that a 10% increase in real GDP growth is associated with a 7.89% rise in the three industries' total R&D growth, significant at 10%. This implies that less constrained industries' total R&D commoves positively with real GDP, consistent with Barlevy's finding that R&D by less constrained firms appear pro-cyclical over aggregate cycle. However, the three industries' total R&D growth displays no significant partial correlation with their total output growth. The seventh row shows that pooling the three industries together returns similar results. In summary, Table 10 suggests that the cyclicality of R&D by less constrained industries over their own cycles differs from that over aggregate cycle, and provide one explanation why our results contrast Barlevy (2007).

6. Technology shocks?

Note that, according to the estimated asymmetric response of R&D to demand shocks, R&D declines *always* when demand fluctuates: it falls in response to demand-driven output increases, and falls again in response to demand-driven output decreases. However, such

results do not imply that R&D never increases, because they only capture R&D's response to demand shocks. As a matter of fact, the estimated correlation of R&D with an increase in output from OLS, as Table 2 shows, is positive, suggesting that other shocks are causing R&D and output to rise together.

What are the likely causes for the increases in R&D? We propose that it is technology shocks. The arrival of new ideas and new technology raises productivity on the one hand, and raises the return to innovation on the other hand by helping a given level of input into R&D activities to generate more ideas and technologies, so that output and R&D increase together. Moreover, given that the bulk of R&D spending is spent on development (Griliches, 1990), firms respond to the arrival of new technology developing them into further productivity gains, which also causes R&D to increase.

Although this explanation is intuitively appealing, it is hard to test it directly, because, as pointed out by the empirical Real Business Cycle literature, measuring technology has long remained as a challenging task (Gali and Rabanal, 2004). Various measures have been proposed, including productivity residuals, patent counts, and newly published books (Basu et.al., 2006; Shea, 1998; Alexopolous, 2006). This section adopts two of them – total factor productivity (TFP) and patent counts – to explore, as the first step, whether controlling for technology would overturn our results of pro-cyclical R&D.

6.1. TFP and Patent Counts

We construct TFP growth by industry using output and inputs data for each sample industry aggregated from the NBER MP database. In particular, it is measured as the growth in output, as the deflated value of shipments, less the weighted growth in total inputs, defined as a Divisia index of capital, production worker hours, non-production workers, materials, and

energy, weighted by factor shares in gross output and measuring the capital share as a residual. An alternative productivity measure is the value-added-weighted aggregate of the four-digit-SIC TFP growth provided directly by MP database. However, the *aggregated* TFP may deviate from the true aggregate TFP due to inter-industry input-output linkages, according to Bartelsman and Gray (1996). Nonetheless, both measures provide quantitatively very similar results.

Data on patents by industry are from the U.S. Patent and Trademark Office (USPTO), which allocates all the utility patents applied and granted in the U.S. between 1963 and 2004 into 41 industries using an OTAF (Office of Technology Assessment and Forecast) concordance between the U.S. Patent Classification System and SIC. [13] The OTAF industries and R&D industries do not fully coincide; aggregating the patenting series according to the R&D industry definitions covers 17 of our sample industries, excluding Lumber (SIC 24, 25), Paper (26), and Other Instruments (SIC 384, 381). We date the patent series by the application date, since, according to the empirical literature, patent applications are superior to patent grants to indicate technology, both because application presumably coincides with the economic viability of an innovation, and because historically there have been long and variable lags between application and granting in the U.S.(Griliches, 1990; Shea, 1998). We restrict the series of patent applications to the years from 1964 to 1998, because the 1963

[13] The early OTAF concordance in the 1970s was criticized of its pervasive double counting (Griliches, 1990). Since the 1980s, however, the USPTO has made a continuous effort to improve the concordance, especially by applying the "fractional-counts" methodology (Griliches, 1990; Hirabayashi, 2003). Alternative concordances include the Yale Technology Concordance by Kortum and Putnam (1997), the Wellesley Technology Concordance by Johnson (2002), and one by Silverman (1999). These concordances map U.S. patents with SIC codes via Canadian industry classifications and International Patent Classification System. While all concordances are subject to some flaws, we choose the OTAF-based patent series because it provides a direct map to the NSF-defined R&D industry groups, as the OTAF was initially established under a contract with the NSF to carry such a task.

observations are implausibly big, and because many patent applications filed from 1999 to 2004 were likely still pending in 2004 and therefore missing in the series of 1999-2004.

6.2. Controlling for technology: OLS

Assuming that technology shocks affect both output and R&D directly, we estimate (2) and (3) by including in the OLS an additional technology control, measured either as TFP growth of patent applications growth.[14] The lagged-technology is included, considering that technology may take time to impact. However, increasing the lag lengths is at the cost of losing observations, because the TFP growth series date back to 1959 and the patent growth series dates back to 1965. We experimented with different lag lengths and find that our results are qualitatively similar, but the cumulative effect usually peaks in a year. We set the lag length at one and report the one-year cumulative impact of technology. Our results with patent applications remain robust to including an additional patent policy control, measured as the growth in the number of patent examiners (Griliches, 1990).

Recall that, under our null hypothesis, R&D declines always with demand shocks, but moves in the same direction with output in response to technology shocks. Therefore, if the growths in TFP or patent applications well captures technology shocks and, and if technology shocks are orthogonal to demand shocks, three results are to be expected by controlling for technology in the OLS. First, the estimated coefficients on technology should be positive in (2) and (3) both. Second, controlling for technology should turn the estimated coefficient on output smaller, because, under the null, technology control removes part of the co-movement

[14] Preliminary panel unit-root test shows that our series in TFP growth are stationary; the series on patent applications contain a unit root in log levels, but are stationary in log-first differences and are not co-integrated. All tests employ industry-specific intercepts, industry-specific time trends, and two lags. Critical values are taken from Levin et al. (2002).

between R&D and output. Moreover, adding the technology control should increase the R-sq significantly, if technology is indeed a key determinant of R&D.

Our results are summarized in Table 10. Technology is measured as TFP growth in Panel 1 and as patent applications in Panel 2. Since the estimations with additional technology controls involve a different sample size, the OLS results with the same set of observations but without technology controls are included in each panel for comparison. A downward arrow by a significant estimate indicates that controlling for technology has turned the point estimate smaller.

Apparently, the null cannot be accepted when technology is measured as growths in TFP. In Panels 1 of Table 10, neither of the estimated coefficients on technology is statistically significant. However, in Panel 2 with technology measured as patent applications, the results are more consistent with the null. The estimated impact of patent applications on R&D is positive and significant: corresponding to a 10% increase in patent applications, R&D rises by 2.14%, significant at 5% level. Adding the technology control increases R-sq from 0.0609 to 0.0763. Moreover, in Panel 2, controlling for technology turns every estimated output coefficient smaller, just as expected under the null. However, the magnitudes of the decreases are small.

6.3. Technology Controls for Machinery and Food

Section 5 finds pro-cyclical R&D for Machinery and mixed cyclicality for Food, while both seem less likely to be financially constrained and thus should have featured counter-cyclical R&D under the opportunity-cost hypothesis with liquidity constraints. One of the possible explanations we proposed was technology shocks are causing R&D to commove positively with output. As a further check on this explanation, we perform simple OLS

estimations of (2) for each of these two industries, adding additional technology controls as TFP or patent applications. Table 11 summarizes the results.

Apparently, the explanation of technology shocks does not work well for Food (SIC 20, 21). The estimated impact of technology on R&D is positive but insignificant when measured as patent applications; it is significant but negative when measured as TFP growth, which is hard to explain. However, for Machinery, the estimated impact of technology is positive and statistically significant with both technology measures. Moreover, controlling for patent applications *weakened* the pro-cyclicality of R&D by Machinery: the estimated output coefficient drops from 0.50 to 0.21, and become statistically insignificant. Most interestingly, controlling for TFP turns the estimated output coefficient negative for Machinery. Panel 2 shows that, without technology control, a 10% increase in output is associated with a 5.02% increase in R&D, significant at 5% level. But after controlling for TFP, it is with a 6.66% *decrease* in R&D, significant at 10% level. Put differently, R&D by Machinery becomes *counter-cyclical* after controlling for TFP growth.

6.4. Discussions

What should we conclude from Table 10 and Table 11? The difficulty remains as that all of these technology indicators are problematic. The TFP growth is technically a residual of output growth. Moreover, it may not reflect technology shocks, but mainly be driven by demand shocks through cyclical utilization (Basu et.al., 2007). Patent application also has its problems in measuring technology. As Griliches (1990) points out, in reality patent applications are usually taken out early during research processes by expecting the long lag between applications and granting. As a result, they coincide more with *innovation effort* rather than innovation outcome. Put differently, the significantly positive estimate on patent

applications may not reflect the response of R&D to technology shocks, but that patent applications are just an alternative measure of R&D. Last but not least, we must acknowledge potential problems with our patent-by-industry series, as the assignment of U.S. patents to industries based on the OTAF concordance cannot be perfect (Griliches, 1990; Kortum and Putnam, 1997).

Therefore, it is difficult to interpret our results on how technology impacts R&D. For example, in Table 10, while controlling for patent applications does decrease the point estimates of the coefficients on output, the magnitudes of the decreases are very small; and R&D's response remains positive. Does it imply that pro-cyclical R&D is caused by some other supply shocks? Or, is that patent applications do not well capture existent technology shocks? Moreover, in Table 11, controlling for TFP growth causes little changes on the cyclicality of R&D by Food, but turns R&D by Machinery counter-cyclical. Do technology shocks matter more for Machinery because new technologies are usually embodied in new machines? We leave such questions for future research.

7. Conclusion

Motivated by the estimation that 86.64% of the observed pro-cyclical aggregate R&D arises from inter-industry comovement, this paper investigates the opportunity-cost hypothesis regarding the "within-industry" 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 that liquidity constraints and technology shocks are important factors in explaining the pro-cyclicality of R&D, and that the negative impact of short-run cycles on long-run

growth can mainly arise from short-run demand fluctuations. We further explore our hypothesis using data on industrial balance sheets, the estimated TFP growth, and patent applications.

Future empirical research should investigate the possibility that technology shocks drive the inter-industry comovement between R&D and output, and explore further R&D's response to technology shocks, either with other technology measures or employing other approaches such as VAR. 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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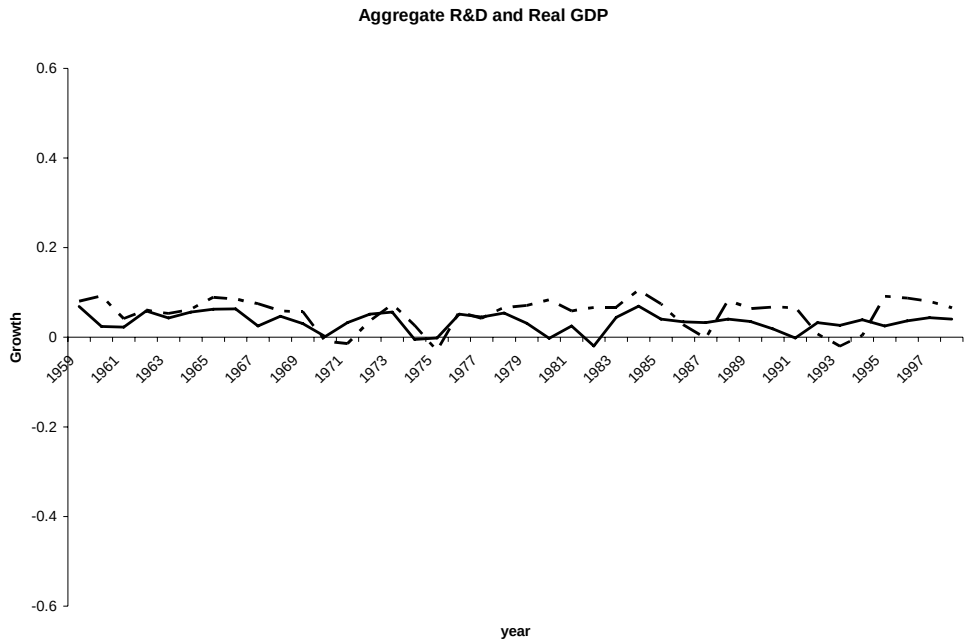
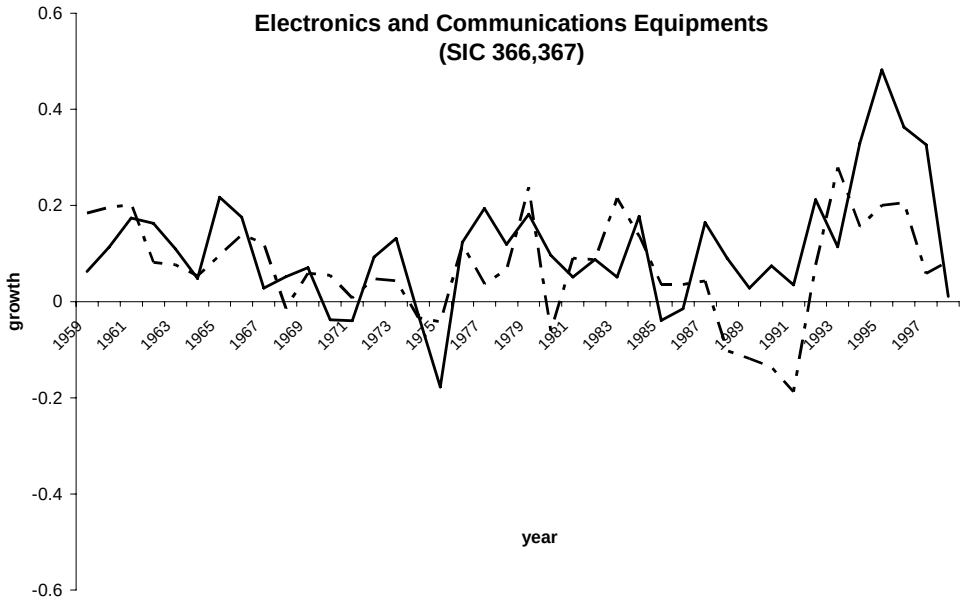
Figure 1

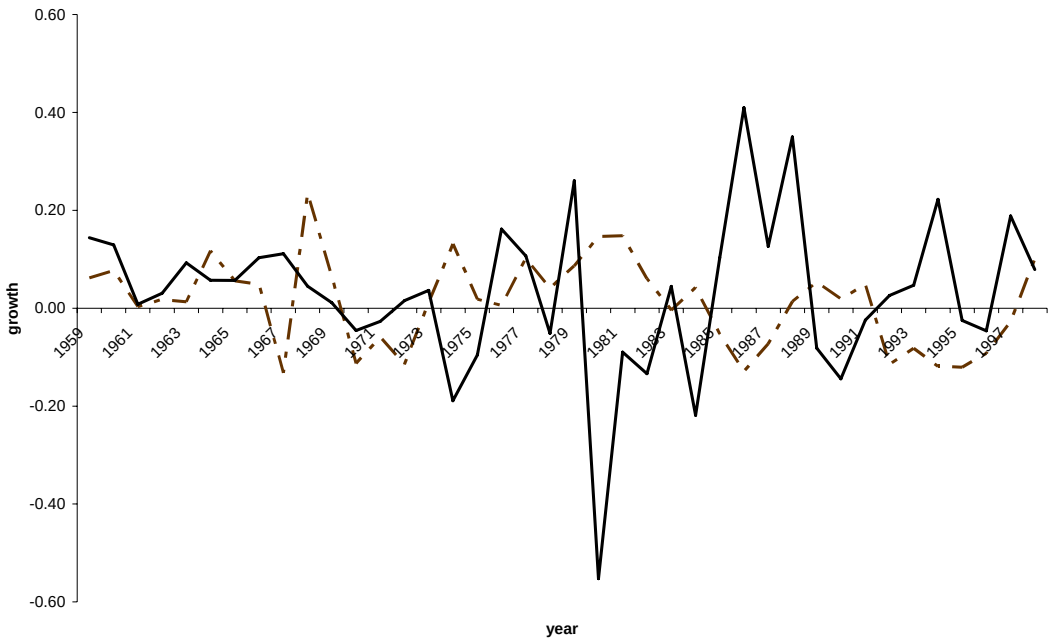




Note: Time-series plots of growth in real R&D expenditure and growth in output for the entire U.S. economy and for one of our sample industries. Solid line denotes output series, dashed line denotes R&D series. See notes to Table 1 and Table 2 for variable definitions and data sources.

Figure 2

Panel 1: Petroleum Refining (SIC 29)



Panel 2: Machinery (SIC 35)

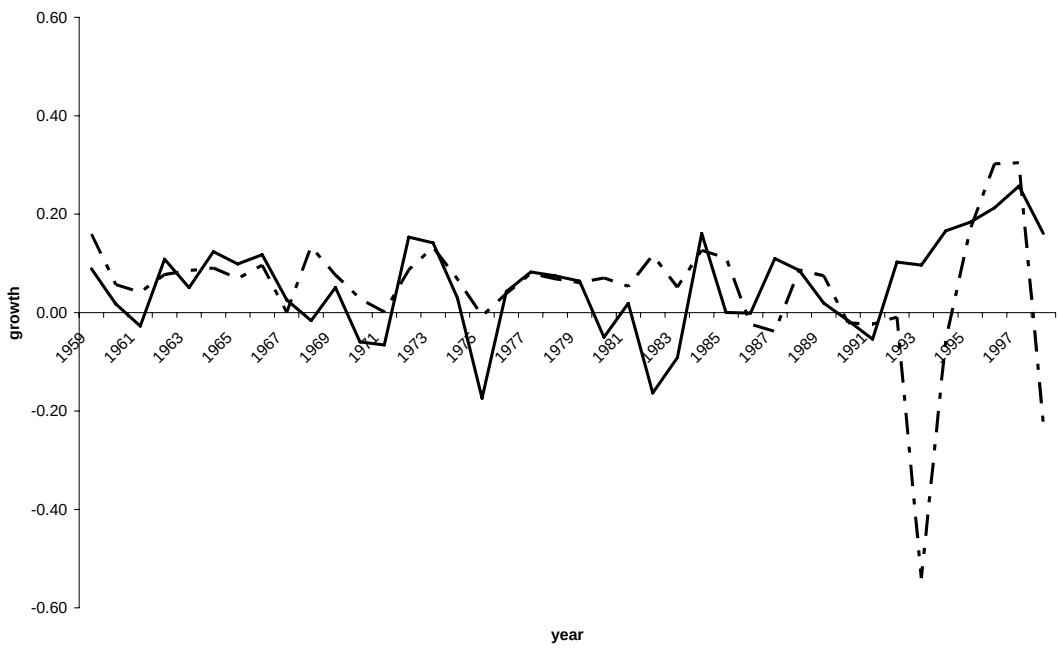
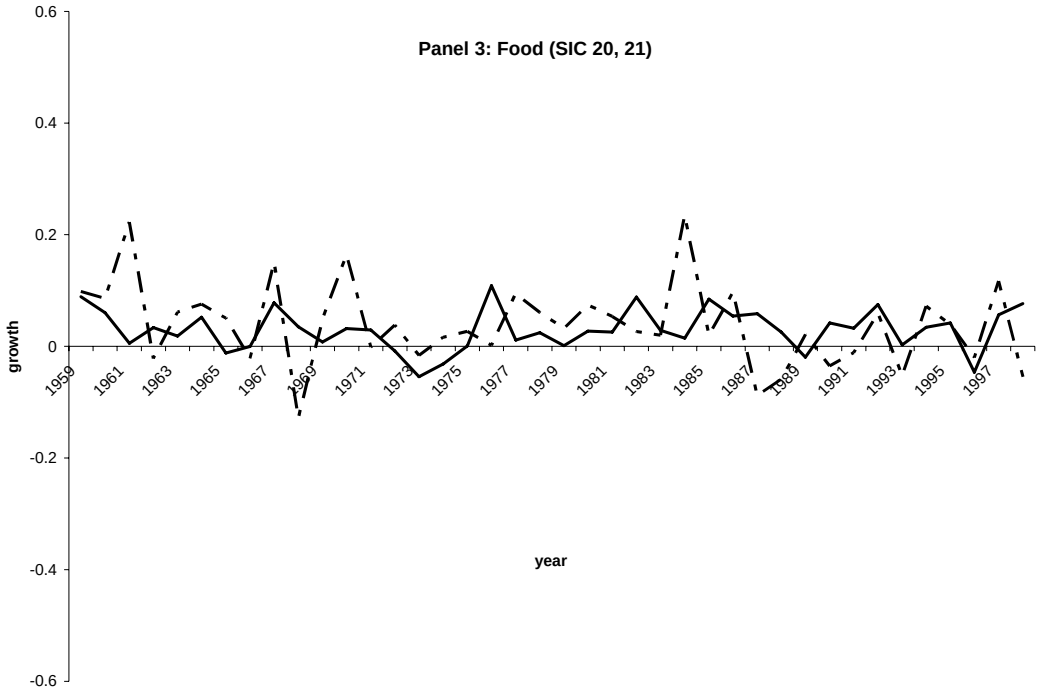


Figure 2 (Continued)



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 2 for variable definitions and data sources.

Table 1: Decomposition of Variances and Covariance Of Aggregate R&D and Real GDP (1958-1998)

	Actual	Estimated	Within-industry	Cross-industry	Cross-industry/ Estimated
Var (agg Y)	4.51×10^{-4}	5.25×10^{-4}	1.90×10^{-4}	3.35×10^{-4}	63.80%
Var (agg R&D)	11.71×10^{-4}	13.00×10^{-4}	9.48×10^{-4}	2.94×10^{-4}	23.36%
Cov(agg Y, agg R&D)	2.44×10^{-4}	2.51×10^{-4}	0.34×10^{-4}	2.18×10^{-4}	86.64%

Notes: R&D is growth in R&D expenditure deflated by the GDP deflator; aggregate Y is measured as real GDP growth. The decomposition is based on (1) in the text, dividing aggregate R&D and output into those by the 20 sample industries in Table 2, and those by "other manufacturing" and "non-manufacturing". Nominal R&D series are from the NSF; the manufacturing output series are compiled from the NBER MP databases, measured as real value added; the non-manufacturing output series are from the BEA. See text for more details.

Table 2: 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 & communication 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%

Table 2 (Continued)

Industrial 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) list 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 3: OLS (20 Industries)

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

OLS3: $R_{it} = \alpha + \beta_1 Y_{it} D_{it}^{H} + \beta_2 Y_{it} D_{it}^{L} + \lambda f(t) + D^{92} + \varepsilon_{it}$

	OLS2			**OLS3**	
	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. OLS2 corresponds to estimations of (2) with lag length of zero, one year, and two years. OLS3 correspond to estimation of (3) 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 4: Aggregate-demand IVs (20 industries)

$$\text{IV2:} \quad R_{it} = \alpha + B(L)Y_{it} + \lambda f(t) + D^{92} + \varepsilon_{it}$$

$$\text{IV3:} \quad R_{it} = \alpha + \beta_1 Y_{it} D_{it}^{H} + \beta_2 Y_{it} D_{it}^{L} + \lambda f(t) + D^{92} + \varepsilon_{it}$$

	IV2			IV3	
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 squares estimations treat output as endogenous and using real GDP and industrial production to instrument for industrial output. IV2 corresponds to estimations of (2) with lag length of zero, one year, and two years. IV4 correspond to estimation of (3) with zero lag allowing coefficient on an increase in output and a decrease in output to vary. Each IV regressions employ the current value and at least one lead of instruments for each output term. See notes to Table 2 for more specifications.

Table 5: Industries and Their Input-Output Instruments

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

Notes: industries, the input-output instruments, and their cost-and-demand relationships. DS is the share of the up-stream industry's output demanded by the down-stream industry, either directly or through other intermediate links; CS is the cost share of the down-stream industry originating from the two-digit sector that contains the up-stream industry, either directly or through other intermediate links. Food (SIC 20, 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 explanations.

Table 6: Input-output IVs (10 industries)

$$\text{IV2:} \quad R_{it} = \alpha + B(L)Y_{it} + \lambda f(t) + D^{92} + \varepsilon_{it}$$

$$\text{IV3:} \quad R_{it} = \alpha + \beta_1 Y_{it} D_{it}^{H} + \beta_2 Y_{it} D_{it}^{L} + \lambda f(t) + D^{92} + \varepsilon_{it}$$

	IV2			IV3	
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 squares 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 one-year lead of the instrument for each output term. All estimations are conducted in growth rates. See notes to Table 2 and Table 3 for more details on modeling specifications; see notes to Table 4 for sample industries and their input-output instruments; see text for more details.

Table 7: Industrial Financial Indicators

Industries ranked by liquid Assets	Liquid Assets (million$)	Net Worth (million$)	With IO IV?
Petroleum (SIC 29)	*14754.12	*183509.58	yes
Machinery (SIC 35)	*16245.76	*132198.96	no
Food (SIC 20, 21)	*11745.77	*101281.77	no
Industry Chemicals (SIC 281-2, 286)	4386.66	63445.07	no
Metal Products (SIC 34)	6419.81	48729.80	no
Paper (SIC 26)	3330.01	48464.70	yes
Drugs (SIC 283)	5833.92	42115.68	yes
Furrous Metals (SIC 331-2, 3398-99)	6113.51	40692.58	yes
Other Chemicals (SIC 284-5, 287-9)	5602.33	40025.26	yes
Non-Ferrous Metals (SIC 333-336)	2684.52	33835.19	yes
Aerospace (SIC 372, 376)	4790.98	33411.20	no
Stones (SIC 32)	3611.92	31138.11	yes
Rubber (SIC 30)	2482.09	24718.18	yes
Lumber (SIC 24, 25)	2171.35	14796.71	yes

Notes: Quarterly average of total liquid assets and net worth of 1960, 1970, 1980, 1990, and 2000 for the 14 sample industries covered by the Quarterly Financial Reports. All numbers are in 2000 dollars. Top three values by each indicator are marked by *. Industries are presented in the order of their rank in net worth. Data on the Quarterly Financial Reports are provided by the Census of Bureau. Values for Lumber (SIC 24, 25) are the average of 1960, 1970, and 2000 only. See text for more details.

Table 8: Liquidity Constraints

Equation 2: $R_{it} = \alpha + \beta Y_{it} + \lambda f(t) + D^{92} + \varepsilon_{it}$

Equation 3: $R_{it} = \alpha + \beta_1 Y_{it} D_{it}^{H} + \beta_2 Y_{it} D_{it}^{L} + \lambda f(t) + D^{92} + \varepsilon_{it}$

	Equation 1	**Equation 2**			**Obs.#**
	Y	YD^H	YD^L	F-test $\beta_1 = \beta_2$	
Panel 1: 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 2: 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 14 financially identified industries and for the three industries less likely to be constrained based on Table 7. 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 2, only Petroleum Refining (SIC 29) possesses valid input-output IV. Standard errors reported in parentheses are controlled for within-industry heteroskedasticity and within-industry arbitrary serial correlation in Panel 1, and controlled for heteroskedasticity only in Panel 2. See notes to Table 3, Table 4, and Table 5 for more details on modeling specifications. See Table 6 for sample industries and their input-output instruments. See text for more details.

Table 9: Liquidity Constraints: Robustness Check

Equation 2: $R_{it} = \alpha + \beta Y_{it} + \lambda f(t) + D^{92} + \varepsilon_{it}$

Equation 3: $R_{it} = \alpha + \beta_1 Y_{it} D_{it}^{H} + \beta_2 Y_{it} D_{it}^{L} + \lambda f(t) + D^{92} + \varepsilon_{it}$

	Equation 1	**Equation 2**			**Obs.#**
	Y	YD^H	YD^L	F-test $\beta_1 = \beta_2$	
Panel 1: Less Constrained Industries by Ratio of Liquid Asset over Total Assets: Food (SIC 20, 21), Petroleum Refining (SIC 29), and Furrous Metals (SIC 331-32, 3398-99)					
OLS	-0.0471 (0.0601)	-0.1600 (0.1282)	0.0236 (0.0708)	1.42 (p=0.2354)	120
Real GDP as IV	-0.0189 (0.1356)	-1.8223 (2.4891)	0.7397 (1.1074)	0.52 (p=0.4724)	120
Industrial Production Index as IV	-0.0640 (0.1282)	-2.3903 (3.6736)	0.9719 (1.7928)	0.38 (p=0.5365)	120
Input-output IV	**-0.2021** (0.0975)**	-0.3872 (1.1091)	-0.1025 (0.6130)	0.03 (p=0.8682)	80
Idiosyncratic input-output IV	**-0.3075** (0.1481)**	-0.1109 (0.5660)	-0.4070 (0.3692)	0.11 (p=0.7385)	80
Panel 2: Less Constrained Industries by Ratio of Net Worth over Total Assets: Drugs (SIC 283), Petroleum Refining (SIC 29), and Machinery (SIC 35)					
OLS	0.0093 (0.0801)	0.1124 (0.1679)	-0.0928 (0.1008)	0.86 9p=0.3562)	120
Real GDP as IV	0.1722 (0.1404)	-1.2005 (1.5346)	0.9446 (0.8493)	0.87 (p=0.3528)	120
Industrial Production Index as IV	0.1411 (0.1205)	-1.5149 (1.9326)	1.2532 (1.3269)	0.75 (p=0.3868)	120
Input-output IV	**-0.2443* (0.1430)**	-0.2987 (0.4192)	-0.1988 (0.3057)	0.02 (p=0.8817)	80
Idiosyncratic input-output IV	**-0.3109*** (0.0023)**	-0.4536 (0.4481)	-0.2179 (0.2761)	0.15 (p=0.6973)	80

Notes: OLS and IV estimates of the relationship between R&D and output from 1958 to 1998 by less constrained industries, identified by two alternative financial indicators. Standard errors reported in parentheses are controlled for heteroskedasticity. See notes to Table 8 for more details.

Table 10: Industry-specific Cycle v.s. Aggregate Cycle: Food, Petroleum Refining, and Machinery

OLS2: $R_{it} = \alpha + \beta Y_t + \lambda f(t) + D^{92} + \varepsilon_{it}$

	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 using the aggregated sample – with the *total* R&D and *total* output of the three industries. The seventh row 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 notes to Table 3 for model specifications; see text for more details.

Table 11: Technology Controls

$$\text{OLS1:} \quad R_{it} = \alpha + \beta Y_{it} + \lambda f(t) + D^{92} + \Pi(L)T_{it} + \varepsilon_{it}$$

$$\text{OLS2:} \quad R_{it} = \alpha + \beta_1 Y_{it} D_{it}^{H} + \beta_2 Y_{it} D_{it}^{L} + \lambda f(t) + D^{92} + \Pi(L)T_{it} + \varepsilon_{it}$$

	Equation 1			**Equation 2**			
	Y	*T*	*R-sq*	YD^H	YD^L	*T*	*R-sq*
Panel 1: industrial TFP growth (774 obs.)							
Without T	0.1397* (0.0695)	-	0.0351	0.1220 (0.1034)	0.1566** (0.0689)	-	0.0337
T=TFP	0.1472 (0.1032)	0.0679 (0.2075)	0.0350	0.1553 (0.1396)	0.1409 (0.0958)	0.0678 (0.2077)	0.0352
Panel 2: growth in industrial patent applications (555 obs.)							
Without T	0.1638** (0.0755)	-	0.0609	0.1395 (0.1193)	0.1853** (0.0729)	-	0.0613
T=Patent Applications	↓0.1436* (0.0726)	0.2144** (0.0747)	0.0763	0.1294 (0.1116)	↓0.1564* (0.0743)	0.2131** (0.0744)	0.0764

Notes: OLS estimates of the relationship between R&D and output after controlling for technology. Technology is measured as five-factor TFP growth in Panel 1, and as patent applications growth in Panel 2. Each regression employs the contemporaneous and the one-year lag of the technology indicator. The reported coefficient on technology is the estimated one-year cumulative effect. Standard errors are controlled for within-industry heteroskedasticity and within-industry arbitrary serial correlations. See notes to Table 3 for more specifications; see text for more details.

Table 12: Technology Controls: Food and Machinery

OLS2: $R_{it} = \alpha + \beta Y_{it} + \lambda f(t) + D^{92} + \Pi(L)T_{it} + \varepsilon_{it}$

	Y	*T*	*No. of Obs.*	*R-sq*
Panel 1: Food				
Without T	0.0269 (0.3123)	-	40	0.1563
T=TFP	-0.1013 (0.4846)	-3.9462** (1.5804)	39	0.2615
T=Patent Applications	0.1716 (0.3693)	0.0799 (0.2261)	33	0.1061
Panel 2: Machinery				
Without T	0.5022** (0.2035)	-	40	0.2101
T=TFP	-0.6658* (0.3793)	3.2329*** (1.0553)	39	0.4072
T=Patent Applications	0.2052 (0.2222)	1.4008** (0.6737)	33	0.3755

Notes: OLS estimates of the relationship between R&D and output, controlling for technology, for Food and Machinery. Each regression employs the contemporaneous and the one-year lag of the technology indicator. The reported coefficient on technology is the one-year cumulative effect. Robust standard errors controlled for heteroskedasticity are reported in parentheses. See notes to Table 11 for more specifications; see text for more details.