R&D, Liquidity Constraint, and the Schumpeterian View

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Abstract

The literature has reached the consensus that pro-cyclical R&D is inconsistent with the Schumpeterian view that predicts innovation to be concentrated during downturns. However, authors disagree on whether liquidity constraint is the explanation. Based on an industry panel of R&D, output, and finance, we document vast differences in industry R&D's cyclicality and find liquidity constraint serves as a useful but not the only explanation. Our results suggest the Schumpeterian view does capture important aspect of innovation's cyclical behavior, but its potential consistency with data is masked by many factors including liquidity constraint.

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1. Introduction

In the past twenty years, a Schumpeterian view of recessions has been revived theoretically by many authors such as Aghion and Saint-Paul (1998), Davis and Haltiwanger (1999) and Aghion et al. (2005). This view argues activities such as R&D, reorganization, and reallocation compete with production for resources, and should be concentrated during recessions when their opportunity cost as forgone output is low. Unfortunately, the Schumpeterian view is often at odds with data. For example, R&D has been repeatedly documented as pro-cyclical at the aggregate level, at the industry level, over the business-cycle frequency, and over the medium-term frequency (Fatas, 2000; Ouyang, 2010; Barlevy, 2007; Comin and Gertler, 2006).[1]

Aghion et al. (2005) propose liquidity constraint as the explanation. They argue firms do desire to concentrate R&D during downturns, but are prevented from doing so by binding liquidity constraints. Aghion et al. (2010) examine a panel of French firms to support this argument; they report R&D is more pro-cyclical for firms with an unfavorable payment history and thus more likely to feature binding constraints. Based on this finding, Agahion et al. (2010) conclude that the presence of binding liquidity constraint is what causes R&D to appear pro-cyclical. However, some authors disagree. Barlevy (2007) studies firm-level data from the Standard and Poor's Compustat database; he finds firm-level R&D is

[1] One may question the basic assumption of the Schumpeterian view that innovative activities complete with production for resources. For example, if innovation utilizes produced goods rather than factor inputs, then optimal R&D should be pro-cyclical. However, Griliches (1990) supports the assumption of the Schumpeterian view, arguing that the major input into R&D is labor, not produced goods.

pro-cyclical regardless of firms' financial positions indicated by cash flow, total assets, fixed assets, short-term debts, and long-term debts. Barlevy (2007)'s finding does not support liquidity constraint as the explanation for the observed inconsistency between R&D's cyclicality and the Schumpeterian view, which motivated many authors to devise alternative models proposing factors determining the cyclicality of R&D other than innovation's opportunity cost (Barlevy, 2007; Francois and Lloyd-Ellis, 2009).

This paper further investigates whether liquidity constraint helps to explain the cyclicality of R&D for the case of the U.S.. We are motivated by the well-known fact that the Compustat database, on which Barlevy (2007)'s finding is based, covers only publicly traded firms that are usually large in size and presumably less constrained financially. This implies a potential sample selection bias in Barlevy's finding. In this paper, we turn to the R&D data by the National Science Foundation (NSF) instead that has been examined by Fatas (2000), Comin and Gertler (2006), and Ouyang (2010a).[2] The NSF R&D data is compiled from an annual R&D survey based on the Standard Statistical Establishment List (SSEL) maintained at the Census. Firms in SSEL are not constrained to be publicly traded: large firms known to conduct R&D regularly are included in advance; additional firms are sampled each year from the remaining firm population; moreover, starting from 1992 the firm-size criterion has been lowered considerably at the purpose of reducing the sample selection bias. While inevitably there is still a bias toward larger firms in the NSF data, such bias should be much milder than that of the Compustat data.

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[2] Barlevy (2007) also examines the NSF R&D data to report the base-line cyclicality of R&D at the aggregate level. However, his exploration of liquidity constraint is based on Compustat databases only.

We examine the NSF published series on R&D by industry, assuming a representative firm for each industry. Data on R&D by industry are combined with the production data from the NBER manufacturing databases and with the finance data from the Quarterly Financial Reports (QFR) published by the Census Bureau. Two financial variables from the QFR are investigated: *liquid assets* as cash and government securities that can be used to finance R&D internally, and *net worth* that can be used as collateral for external borrowing. Following Ouyang (2010a), we investigate the cyclicality of R&D as the correlation between industry R&D and industry output, taking advantage of the fact that industry cycles are not fully synchronized. Then we explore whether industry financial strength helps to explain differences in industry R&D's cyclicality cross-section, and whether cyclical R&D reflects variations in industry financial positions over the output cycle.

Our findings are as follows. Cross-section, R&D's cyclicality differs vastly across industries, ranging from being pro-cyclical, a-cyclical, to counter-cyclical. Industry financial strength can explain *some* but not *all* of the differences. In particular, Petroleum Refining is the only industry with counter-cyclical R&D: its financial strength is also the strongest according to the net-worth indicator. However, Petroleum Refining falls behind some other industries according to the liquid-asset indicator. This provides mixed evidence on the liquidity-constraint explanation for pro-cyclical R&D.

Interestingly, our panel estimation generates some interesting new results that shed light on the impact of liquidity constraint on R&D's cyclicality. One the one hand, we find variations in industry liquid-asset positions indeed have no influence on the cyclicality of R&D, consistent with findings by Barlevy (2007). On the other hand, we find industry R&D growth *tracks* industry net-worth growth; for industries displaying pro-cyclical R&D on average, controlling for net-worth growth turns their R&D acyclical. We interpret this result as that the impact of binding liquidity constraint on R&D's cyclicality is also present in the U.S., and that net-worth growth better captures cyclical financial factors influencing R&D's cyclicality.

Unfortunately, even after controlling for net-worth growth, R&D still fails to appear counter-cyclical as the Schumpeterian view suggests. This suggests there must be other factors masking the potential consistency, if any, between the Schumpeterian view and R&D's cyclicality. We explore one additional factor proposed by Ouyang (2011a) – output persistence. Measuring output persistence as the AR(1) coefficient of industry output growth, we find R&D does turn counter-cyclical after controlling for *both* industry finance *and* output persistence, although persistence alone fails to do so. We interpret this result as the Schumpeterian view does capture important aspects of the cyclicality of R&D, but its potential consistency with the data is masked by many factors including liquidity constraints.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 presents the results. Section 4 concludes.

2. Data

Data on R&D by industry is from the NSF that publishes annual R&D expenditure for 20 major manufacturing industries based on the 1987 Standard Industry Classification (SIC) starting from 1958. [3]

[3] Some industry-year observations in the R&D panel are suppressed to avoid disclosure of individual firms' operations. Following Shea (1998), the growth of total R&D including both company-financed and federal-financed is used to interpolate gaps in the series of company-financed R&D. There are three cases where the

The R&D panel is truncated by the year of 1998, because later series are compiled based on the North American Industry Classification System (NAICS). According to the NSF, converting the R&D-by-industry series under the SIC into those under the NACIS or vice versa involves considerable errors and thus is not recommended.[4] The NSF R&D data is heavily dominated by the manufacturing R&D, both because the manufacturing sector is an important innovating sector and because the NSF R&D survey was designed back in the 1950s when the U.S. economy was largely manufacturing based.

Data on industry Finance is from the QFR by the Census Bureau that publishes income statements and balance sheets for major manufacturing industries. Unfortunately, only 16 out of the 20 R&D industries are covered by the QFR. Moreover, the QFR before 1987 is not available in electronic format, so that obtaining a full panel involves manually inputting data based on hard copies of the QFR before 1987. Two variables are chosen from the QFR financial statements to be included in this panel: the level of liquid assets as cash and U.S. government securities and the level of net worth.

Data on output are from the NBER manufacturing productivity (MP) database with annual data on production for manufacturing industries from 1958 to 2002. Because the MP database is provided at the four-digit SIC level and the NSF R&D data is published at the two-digit and the combinations of the three-digit level, we are able to aggregate the production data based on the NSF definitions of industries.

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observations on the total R&D spending are also missing, we use growth in company-financed R&D at higher SIC level for interpolation.

[4] See http://www.nsf.gov/statistics/srs01410/.

Combining the NSF R&D data, the MP production data, and the Census QFR data gives us an annual panel of R&D, production, net worth, and liquid asset for 16 manufacturing industries from 1958 to 1998.

We use real company-financed R&D expenditure to measure innovation. Following Barlevy (2007) and Ouyang (2010a), the nominal R&D series are converted into 2000 dollars using the GDP deflator. We deflate nominal R&D by the GDP deflator instead of the industry output price because R&D expenditure reflects the cost of research scientists or equipments rather than that of the output price.[5] Output is measured as real value added, as the deflated value added using shipment-value-weighted price deflator. We measure output as real value added instead of real value of shipments (sales) because the latter is influenced by cyclical inventory adjustment.[6] Nonetheless, our results are in general robust to measuring output as real value of shipments. The values of net worth and liquid asset are also converted into 2000 dollars using the GDP deflator.

The 16 sample industries, together with their SIC codes, are listed in Column 1 of Table 1. Ouyang (2010a) argues the cyclicality of industry R&D should be conducted over the industry cycle, both because the Schumpeterian view analyzes how firms balance inter-temporarily their *own*

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[5] Barlevy (2007) shows the real R&D expenditure deflated by the GDP deflator and the number of full-time equivalent R&D scientist and engineers show similar cyclical patterns. The NSF also publishes data on the number of full-time equivalent R&D scientist and engineers by industry, which, however, involves a large number of missing observations to avoid disclosure of operational information.

[6] Wen (2005) documents pro-cyclical inventory investment over the business-cycle frequency: firms accumulate inventory when production is high and withdraw inventory when production is low. This suggests high sales do not necessarily imply high production, but the major implication of the Schumpeterian view is inter-temporal balance of production and innovation.

innovation and production, and because the industry cycles are not fully synchronized with the aggregate cycle. This is shown by Column 2 of Table 1 that presents the 1958-1998 time-series correlation coefficients between industry output growth and the real GDP growth over the sample period. The coefficient ranges from -0.0289 for Food (SIC 20 and 21) and 0.8467 for Stones (SIC 32). The vast difference in the correlation between industry output and aggregate output suggests fluctuations at the industry level do no simply reflect those at the aggregate level: they are possibly driven by industry-specific shocks or by that industries respond differently to common aggregate shocks. Therefore, examining the cyclicality of industry R&D over the aggregate cycle is subject to an aggregation bias. For example, since the industry cycle of Food moves against the aggregate cycle, R&D by Food may appear pro-cyclical over the aggregate cycle even if Food companies do concentrate their R&D when Food output is low.

Before we proceed to estimate the cyclicality of industry R&D, we perform 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 the series of real R&D expenditure, of real value added, of real liquid assets, and of real net worth contain a unit root in log levels, but are stationary in log-first differences and are not co-integrated. Therefore, we employ log-first differences (growth rates) in R&D, in output, in net worth, and in liquid asset in all the estimations.

3. R&D and Liquidity Constraint

We conduct empirical investigation in two steps. First, we investigate whether the cyclicality of industry R&D is correlated with industry financial strength cross-section. Under the null of liquidity constraint, financially strong industries should feature non-binding constraints and thus counter-cyclical R&D. Then, we run a panel regression to estimate whether cyclical variations in industry R&D reflect changes in industry financial positions over the cycle, and whether controlling for financial positions uncovers cyclical patterns of R&D consistent with the Schumpeterian view.

3.1 The Cyclicality of Industry R&D

Table 1 reports the cyclicality of industry R&D for 16 sample industries in Columns 3-5. Column 3 lists the 1958-1998 time-series correlation coefficients between R&D growth and output growth by industry. Columns 4-5 present the estimated cyclicality of industry R&D based on the following specification:

$$(1) \Delta lnR_{it} = \alpha_i + \beta_i \Delta lnY_{it} + \gamma_i X_t + \varepsilon_{it}.$$

$\Delta \ln R_{it}$ is the R&D growth for industry *i* in year *t*. $\Delta \ln Y_{it}$ is the output growth. X_t is a set of controls including a quadratic trend and a post-1992 dummy. The quadratic time trend is allowed to differ before and after 1980 at the purpose of capturing changes in aggregate volatility referred as the Great Moderation in the literature (McConnell and Perez-Quiros, 2000); the post-1992 dummy presumably reflects the impact of a drop in the criterion on firm size in the NSF R&D survey starting from 1992. ε_{it} is the error term. Intuitively, (1) estimates the contemporaneous correlation between industry R&D

growth and output growth. We do not include output lags to avoid reducing the degrees of freedom, but the results are robust to including additional output lags.[7]

We run the OLS regression of (1) industry by industry, with and without X_t. The sample size of each regression is 40. The OLS estimates of β_i without controlling for time trends and the post-1992 dummy are reported in Column 4 of Table 1; those with controls are presented in Column 5. We also run OLS regression of (1) by pooling industries together, imposing common β and γ but allowing α_i to differ as industry dummies. The pooled sample size is 640. The estimates on β with pooled sample are presented in the bottom row of Table 1.

Column 3 of Table 1 reports five negative and 11 positive coefficients out of the 16 time-series correlation coefficients between industry R&D growth and industry output growth. The average coefficient equals 0.0818, implying mild pro-cyclicality on average. Column 4 reports, without additional controls, five out of the 16 estimates are negative, one is statistically significant at the 1% level; 11 are positive, five are statistically significant at the 10% level or above. Pooling industries together produces a statistically insignificant estimate of 0.0854. Column 5 presents very similar results with quadratic time trends and a post-1992 dummy included as additional controls.

The cyclicality of industry R&D reported in Table 1 is qualitatively consistent with those documented by the existing literature. In the case of the U.S., Barlevy (2007) regresses aggregate private

[7] The estimated coefficients on output terms lagged one-three years are statistically insignificant, while the cumulative estimates are. Details are available upon request.

R&D growth on a constant and real GDP growth, and reports an estimated coefficient of 0.69 on real GDP growth; Ouyang (2010a) runs a 20-industry panel regression, and estimates the output coefficient to be 0.1351; the two estimates by Barlevy (2007) and Ouyang (2010a) are both statistically significant at the 10% level or above. In Table 1, the estimated output coefficients based on the pooled sample are positive, but compared to those by Barlevy (2007) and by Ouyang (2010a), they are smaller in point estimates and statistically insignificant. The quantitative difference between R&D's cyclicality at the aggregate level and that at the industry level arises from an aggregation bias due to inter-industry R&D-output comovement (Ouyang, 2011b).[8] Our estimated average cyclicality of industry R&D is milder than that reported by Ouyang (2010a), because several industries with pro-cyclical R&D are not covered by the QFR and thus missing from our sample.[9]

Table 1 provides mixed evidence for the Schumpeterian view that R&D is concentrated when output is low. Instead, it shows vast differences in the cyclicality of R&D across industries. According to our estimates, R&D is strongly pro-cyclical for industries such as Stones (SIC 32) and Aerospace (SIC 372 and 376): their estimated output coefficients are over 0.50 and statistically significant at the

[8] Ouyang (2011b) decomposes aggregate R&D and output in the U.S. into those by 22 industry groups, and find inter-industry comovement accounts for over 94% of the procyclicality of aggregate R&D and amplifies the average pro-cyclicality of industry-level R&D by about five times.

[9] These are Textiles (SIC 22 and 23), Autos and Others (SIC 371, 373-75, 379), Scientific Instrument (SIC 381,382), Other Instrument. (SIC 384-387), Electronic Equipment (SIC 366-367), and Other Equipment (SIC 361-365, 369). The QFR reports finance data for Electronics (SIC 36) and Instruments (SIC 38) as two-digit sectors. Therefore, according to the QFR we aggregate R&D data and output data by Scientific Instrument and by Other Instrument into those by Instrument (SIC 38), and those by Electronic Equipment and by Other Equipment into those by Electronics (SIC36).

5% level or above. However, R&D by Petroleum Refining (SIC 29) *is* indeed counter-cyclical: the estimated coefficient on Petroleum Refining output growth is -0.1743 without additional controls, significant at the 1% level, and -0.1264 with additional controls, significant at the 5% level. Figure 1 presents the time-series plots of R&D growth and output growth for Petroleum Refining from 1958 to 1998: the two curves display negative co-movement over time with a time-series correlation coefficient of -0.3144.

The counter-cyclicality of Petroleum Refining R&D may seem surprising at first. However, similar pattern is also documented by Barlevy (2007) who reports a negative correlation between Petroleum R&D growth and real GDP growth (Figure 3, page 1139). Why Petroleum Refining R&D is counter-cyclical unlike R&D by other industries is an interesting phenomenon, and can intrigue many explanations. One may question whether Petroleum Refining is itself a counter-cyclical industry over the aggregate cycle, possibly due to fluctuations in oil prices. However, Column 2 of Table 1 reports Petroleum Refining output growth displays a positive correlation coefficient of 0.4159 with real GDP growth. Moreover, it is hard to argue theoretically why oil-price shocks should influence the cyclicality of R&D differently, as they raise the production cost, lower the production profit, and reduce the opportunity cost of R&D just like other production shocks. Counter-cyclical Petroleum Refining R&D is indeed consistent with the Schumpeterian view.

3.2 Industry Financial Strength

We explore whether the cross-section differences in industry financial strength helps to explain the cross-section differences in industry R&D's cyclicality. Industry financial strength is approximated using values of net worth and liquid assets, both deflated by the GDP deflator. Ouyang (2010a) argues Petroleum Refining possesses superior financial strength relative to other industries, showing the time-series average of total real net-worth value by Petroleum Refining far exceeds those of other sample industries and its total liquid-asset value is ranked only after Machinery (SIC 35). However, the total net-worth or liquid-asset value reflects not only industry financial strength but also industry size. Bigger industries like Machinery can require a large amount of financial resources for regular production, so that high total net-worth or liquid-asset value does not necessarily imply their liquidity constraints are less likely to bind. Therefore, we measure industry financial strength in ratios. In particular, we generate two ratios, N_i and L_i, to indicate industry i's financial strength:

$$(2) N_i \equiv \frac{Real\ Net\ Worth_i}{Size_i}, L_i \equiv \frac{Real\ Liquid\ Asset_i}{Size_i}$$

The numerators in (2) are the 1958-1998 quarterly averages of net worth value and liquid asset value in 2000 dollars. $Size_i$ is the size of industry i. We measure $Size_i$ as the 1958-1998 average annual real production value of industry i, which equals the sum of real value added and real value of raw materials. The idea is that industries like Petroleum Refining may spend a large amount of liquid asset on purchases of raw materials, so that including value of raw materials in measuring industry size better evaluates an industry's possibility of having binding liquidity constraints. Columns 2 and 3 of Table 2 present values of N_i and L_i. The top three values are in bold. Petroleum Refining possesses the highest net-worth ratio equal to 1.5799, more than twice of the cross-industry mean of 0.7000; its liquid-asset ratio equals 0.1270, well above the cross-industry mean of 0.0759 but lower than those of Drugs (SIC 284) and Electronics (SIC 36).[10]

According to the net-worth ratio, Table 2 provides one reasonable explanation for counter-cyclical Petroleum Refining R&D: firms do desire to concentrate R&D during low-production times, but only those with sufficiently strong financial strength and non-binding constraints are able to optimize the timing of R&D as they desire. Petroleum Refining may be the only industry with non-binding constraint by possessing the highest net-worth ratio. Thus, binding liquidity constraint can be what drives R&D pro-cyclical for most other industries as well as at the aggregate level.

However, the liquid-asset ratio of Petroleum Refining falls behind those by Drugs and by Electronics. According to Table 1, for Electronics, R&D is pro-cyclical with positive and statistically significant estimates on the output coefficient either with or without additional controls; for Drugs, the estimated output coefficients, although both statistically insignificant also remain positive either with or without additional controls. This, together with the relatively strong financial strength of Drugs and Electronics suggested by Table 2, does not support liquidity constraint as the explanation for pro-cyclical R&D.

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[10] One may argue that average level of industry R&D spending should be applied to divide the values of net worth or liquid asset to indicate industries' ability to finance R&D. However, with binding liquidity constraint, financially weaker industries feature lower levels of R&D spending. This is true in our panel: regressing the industry R&D level on any of the financial indicators and a constant generates positive and significant estimate on financial indicators, even after controlling for industry size either measured as real value added or real production value. This suggests the ratios of net worth or liquid asset over the R&D level should underestimate the financial strength of financially strong industries but overestimate that of financially weak industries.

3.3 Panel Evidence

The cross-section analysis is based on the estimation of R&D's cyclicality industry-by-industry. The sample size of each regression is only 40, making it difficult to interpret the insignificant estimates on the output coefficient for many industries reported in Table 1. Do they imply acyclical R&D? Or is the sample size just too small to detect an existent pro-cyclicality or counter-cyclicality? In this subsection we pool sample industries together to run panel estimations specified as follows:

$$(3)\Delta lnR_{it} = \alpha_i + \beta\Delta lnY_{it} + \gamma X_t + \varepsilon_{it}$$

α_i is the industry dummy. X_t is a set of exogenous controls including a quadratic time trend allowed to differ before and after 1980 and a post-1992 dummy as in (1). Under this specification, estimate on β reflects average cyclicality of industry R&D, namely, the extent to which deviations from mean R&D growth correlate with deviations from mean output growth on average. Our results are robust to dropping X_t, replacing X_t with year dummies, including additional output lags, or controlling for lagged R&D growth.

As suggested by the cross-section evidence, Petroleum Refining is the only industry with counter-cyclical R&D and thus likely the only industry with non-binding liquidity constraint. Accordingly, we run OLS regressions of (3) with and without Petroleum Refining. The results are summarized in Panel A of Table 3. For the 16-industry panel including Petroleum Refining, the OLS estimate on β is positive but statistically insignificant. This result is also reported in the bottom row of Column 5 of Table 1. However, once Petroleum Refining – the only industry with counter-cyclical R&D – is excluded from the sample, the OLS estimate on β becomes much bigger in point estimates and turns significant at the 5% level. A 10% increase in industry output growth is estimated to be associated with a 1.52% increase in industry R&D growth, suggesting pro-cyclicality of R&D on average. This point estimate is very close to that of 0.1351 reported by Ouyang (2010a) based on the 20-industry panel.

Under the null of liquidity constraint, R&D appears pro-cyclical by picking up variations in industries' ability to finance R&D that is positively correlated with industry output. In that case, the positive estimate on the output coefficient by (3) captures the impact of some omitted measures of industry financial position that varies over the cycle; including these measures should reduce or eliminate the average pro-cyclicality of industry R&D. We apply two measures to indicate variations in industry financial position. The first measure, denoted by ΔlnQ_{it}^{1}, is the annual growth in industry real net worth level. The second measure, denoted by ΔlnQ_{it}^{2}, is the annual growth in industry real liquid asset holdings. Since QFR publishes industry balance sheets on a quarterly base, we convert quarterly data to annual data by taking the four-quarter average, although measuring ΔlnQ_{it}^{1} and ΔlnQ_{it}^{2} as growth from the fourth quarter to the fourth quarter gives very similar results. Following Aghion et al. (2005, 2010), two additional interaction terms are included to capture the influence of the cross-section difference in industry financial strength on R&D's cyclicality: $N_i\Delta lnY_{it}$ and $L_i\Delta lnY_{it}$. Specifically, we estimate the following:

$$(4)\Delta lnR_{it} = \alpha_i + \beta\Delta lnY_{it} + \theta_1\Delta lnQ_{it}^{1} + \theta_2\Delta lnQ_{it}^{2} + \varphi_1 N_i\Delta lnY_{it} + \varphi_2 L_i\Delta lnY_{it} + \gamma X_t + \varepsilon_{it}$$

Under the null of liquidity constraint, $\theta_1>0$ and $\theta_2 >0$ as industry R&D growth co-moves positively with variations in industries' ability to finance R&D; moreover, $\varphi_1<0$ and $\varphi_2<0$ as industries with higher N_i or L_i tend to feature counter-cyclicality or weaker procyclicality of R&D. We run the OLS panel regression of (4) with and without Petroleum Refining. The results are robust to including additional output lags, additional lagged financial variables, or replacing industries dummies by N_i or L_i .

[11] All details are available upon request. Column 2 of Panel B, Table 3, reports the results for the 16-industry panel; Column 3 reports those for the 15-industry panel excluding Petroleum Refining. We summarize these results as follows.

First, the estimates on θ_1 are positive and statistically significant at the 5% level for both panels, suggesting industry R&D growth co-moves positively with industry net-worth growth. In particular, a 10% increase in net-worth growth is associated with a 0.10% increase in R&D growth when Petroleum Refining is included and with a 0.18% increase in R&D growth when Petroleum Refining is excluded. The bigger point estimate for the 15-industry panel imply stronger relationship between R&D and net-worth for industries whose liquidity constraints are more likely to bind. This is consistent with the null of liquidity constraint.

Second, controlling for cyclical variations in industry financial position *eliminates* the average procyclicality of R&D for the 15-industry panel. In Column 2 of Panel A, β is positive and significant at the 5% level; in Column 2 of Panel B, β becomes much smaller in point estimate and turns statistically insignificant *after* controlling for industry finance. This implies the average pro-cyclicality of R&D for 15 industries reflects better financial positions when output is high or worse financial positions when output is low. This is, again, consistent with the null.

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[11] Experimentations with other specifications show that the estimated coefficients on lagged output growth, on lagged net-worth growth, on lagged liquid-asset growth, or on lagged R&D growth are always statistically insignificant. We also tried including the ratios of real liquid asset or real net worth over real production value as panel variables (N_{it} and L_{it}) in the regression, and find their estimated coefficients are statistically insignificant under various specifications. Note N_{it} and L_{it} rise only when net worth and liquid asset rise more than production, which might under-evaluate improvement in financial positions. All results are available upon request.

Third, with Petroleum Refining included in the panel, the estimate on φ_1 is negative and significant at the 5% level. With Petroleum Refining excluded, the estimate on φ_1 remains negative but becomes statistically insignificant. This is consistent with the cross-section evidence pointing to Petroleum Refining as possibly the only industry with non-binding liquidity constraint. The differences in other industries' financial strength measured by N_i might not be vast enough to account for differences in their R&D's cyclicality.

Fourth, the estimated coefficients on liquid-asset growth, θ_2, are positive but statistically insignificant in both panels, implying R&D's cyclicality is uncorrelated with liquid-asset growth. The two estimates on φ_2, the coefficient on $L_i \Delta lnY_{it}$, are both positive; one is significant at the 10% level. The positive estimate on φ_2 is the opposite of what the liquidity-constraint hypothesis predicts, and is hard to explain. However, the positive estimate on φ_2 is not robust: excluding Petroleum Refining renders this estimate insignificant as reported by Column 3 of Panel B; experimentation shows leaving out $N_i \Delta lnY_{it}$ also turns the estimated φ_2 negative and insignificant.

3.4 Liquidity Constraint

The results reported in Panel B of Table 3 are consistent with the null of the liquidity constraint, but only when industry finance is indicated by net worth. The result that R&D growth does not track liquid-asset growth is consistent with Barlevy (2007)'s finding that R&D growth and cash flow display no significant contemporaneous correlation for Compustat firms.[12] However, Hall (1992) reports a large and positive elasticity between R&D and cash flow for U.S. manufacturing firms. Note liquid-asset growth differs from cash flow by definition: liquid-asset growth is the percentage increase in liquid-asset holdings recorded by financial statements, while cash flow is calculated from income-statement variables such as revenue and operational costs. Brown and Petersen (2010) regress R&D growth on both cash flow and changes in cash holdings; they report the estimated coefficient on cash flow is significantly positive but that on changes in cash holdings is significantly *negative* (Tables 4 and 5); they interpret this result as that firms use cash holdings to smooth R&D over time. Brown and Petersen (2010)'s finding suggests the correlation between R&D growth and liquid-asset growth can be ambiguous even under the null of liquidity constraint: improvements in financial positions can be associated with rises in liquid-asset holdings on the one hand as firms get more cash inflow, and declines in liquid-asset holdings on the other hand as firms free liquid to raise R&D spending or other capital investments.

Moreover, recall the cross-section evidence shows the liquid-asset ratio does not perform well when explaining differences in industry R&D's cyclicality. This suggests liquid asset may not be a good indicator for industry financial strength either: an industry can hold a large amount of liquid asset not because it is financially flexible, but because its regular operation requires constant cash flow.

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[12] Barlevy (2007) also reports lagged cash flow, although showing no influence on R&D's cyclicality, does impact the level of R&D spending. However, our experimentation with including lagged liquid-asset growth in estimating (4) suggests the estimated coefficients on liquid-asset growth, either contemporary or lagged by one to three years, remain statistically insignificant.

Therefore, we argue, based on both cross-section and panel evidence, that net worth better captures financial factors influencing the cyclicality of R&D.

4 On the Schumpeterian View

The results in Table 3 imply the presence of liquidity constraint's impact on R&D's cyclicality. However, they also raise further questions. For example, according to Panel B of Table 3, the estimated output coefficients are statistically insignificant after controlling for industry finance, which is, once again, inconsistent with the Schumpeterian view. If binding liquidity constraint is what causes the inconsistency between the cyclicality of R&D and the Schumpeterian view, then the output coefficient should be negative after controlling for finance.

Nonetheless, liquidity constraint cannot be the only factor influencing R&D's cyclicality aside from R&D's opportunity cost. This has been pointed out by many authors. Barlevy (2007) posits that the dynamic externality inherent to the innovation process drives the return to R&D short-term, so that firms innovate more when producing more. Francois and Llyod-Ellis (2009) model innovation as a three-stage process in which R&D spending rises during the implementation boom. This suggests, due to various factors, R&D may not be counter-cyclical even in the absence of binding liquidity constraints.

4.1 Cyclical Persistence

Ouyang (2011a) proposes one additional factor influencing R&D's cyclicality -- cyclical persistence. She argues innovation's cyclical pattern should be determined jointly by two factors: the cyclicality of innovation's marginal opportunity cost emphasized by the Schumpeterian view, *and* the cyclicality of innovation's marginal expected return. The cyclicality of R&D should be determined by the relative magnitude of the volatilities of the two factors which, in turn, is influenced by cyclical persistence. We sketch Ouyang (2011a)'s idea in a simple model as follows.

A representative entrepreneur lives for two periods. In period one, she produces and innovates; in period two, she implements the innovation outcome if innovation turns out successful, produces, and dies. Suppose the entrepreneur is endowed with a fixed amount of labor normalized as one each period. Let *E* to be the production labor and *R* to be the innovation labor: *E+R=1* in period one; *E=1* in period two. The entrepreneur produces according to the following production function:

$$(5) Y = A\varepsilon E^{\alpha}, 0 < \alpha < 1$$

A is an endogenous productivity; ε is a cyclical production shock that follows a Markov process with $E(\varepsilon_{t+1}|\varepsilon_t) = {\varepsilon_t}^{\rho}$, where ρ captures the cyclical persistence. *R* unit of innovation labor in period one gives a probability of φR for innovation to be successful. With successful innovation, the entrepreneur pays a cost C *by the end of period one* to adopt the innovation outcome into period-two production, which updates *A* by a factor λ. With unsuccessful innovation, the entrepreneur continues to produce at *A*. Under this setup, in period one the entrepreneur maximizes the following value function by choosing the appropriate *R*:

$$(6)\ V(R, \varepsilon) = A\varepsilon(1 - R)^{\alpha} + \frac{(1 - \varphi R)}{(1 + r)} A\varepsilon^{\rho} + \varphi R \left(\frac{\lambda A\varepsilon^{\rho}}{(1 + r)} - C\right)$$

The first-order condition of (6) with respect to *R* yields:

$$(7)\ \varepsilon\alpha(1 - R)^{\alpha - 1} = \frac{\varphi(\lambda - 1)}{(1 + r)}\varepsilon^{\rho} - \varphi\frac{C}{A}$$

The left-hand side of (7) reflects the marginal opportunity cost of innovation, and the right-hand side captures the marginal expected return to innovation net of the (expected) adoption cost normalized by *A*. Ouyang (2011a) and Ouyang (2011b) model liquidity constraint as the entrepreneur's ability to finance *C*. To see how cyclical persistence influences innovation's cyclicality *in the absence of the liquidity constraint*, we set *C=0* and take the logs of both sides of (7):

$$(8)\ \ln(1-\mathrm{R}) = \frac{1}{(\alpha-1)} ln\left[\frac{\varphi(\lambda-1)}{\alpha(1+r)}\right] + \frac{1}{(1-\alpha)} ln(\varepsilon) - \frac{\rho}{(1-\alpha)} ln(\varepsilon)$$

The first term on the right-hand side of (8) is a constant; the second term, $\frac{1}{(1-\alpha)} ln(\varepsilon)$, comes from the log of the marginal opportunity cost of innovation; the third term, $\frac{-\rho}{(1-\alpha)} ln(\varepsilon)$, rises from the log of the marginal expected return to innovation. Since $\ln(1-R)$ declines in *R*, (8) suggests optimal innovation is *negatively* correlated with $ln(\varepsilon)$ but *positively* related to $\rho ln(\varepsilon)$. Put intuitively, innovation in the absence of liquidity constraint should be concentrated when the *present* production shock is low but when the *expected future* production shock is high. Taking the differences of (8) yields:

$$(9)\Delta ln(1-R) = \frac{1}{(1-\alpha)}\Delta ln(\varepsilon) - \frac{\rho}{(1-\alpha)}\Delta ln(\varepsilon).$$

4.2 R&D, Persistence, and Liquidity Constraint

We approximate $\Delta ln(\varepsilon)$ using output growth to estimate persistence. In particular, we estimate ρ_i as the AR(1) coefficient of industry output growth:

$$(10)\ \Delta lnY_{it} = \rho_i \Delta lnY_{it-1} + \epsilon_{it}$$

(10) is estimated industry by industry, measuring ΔlnY_{it} as growth in industry real value added.[13] ϵ_{it} is the error term. Under the specification of (10), expected production growth one period ahead, $E(\Delta lnY_{it}|\Delta lnY_{it-1})$, equals $\rho_i \Delta lnY_{it-1}$. With $\widehat{\rho_i}$ as the OLS estimate on ρ_i for industry *i* based on (10), we explore how persistence influences industry R&D's cyclicality by estimating the following:

$$(11) \Delta lnR_{it} = \alpha_i + \beta \Delta lnY_{it} + \lambda \widehat{\rho_i} \Delta lnY_{it} + \gamma X_t + \varepsilon_{it}.$$

X_t is a set of controls as in (1) and (3). α_i is an industry dummy capturing factors such as the employment level in industry i. (11) estimates the correlation between innovation and contemporaneous production, controlling for the expected future production. Under the null, $\beta<0$ and $\lambda>0$: innovation is concentrated when the present production is low but the expected future production is high. We estimate (11) employing our industry panel with and without Petroleum Refining.

The results are summarized in Panel A of Table 4. The estimated coefficients on $\widehat{\rho_i} \Delta lnY_{it}$ with and without Petroleum Refining are both positive and statistically significant at the 1% level. This suggests R&D by industries with higher persistence tends to appear more pro-cyclical; put differently, it implies R&D is concentrated when the *expected* future production is high. Interestingly, a similar pattern has been reported by Barlevy (2007): he finds R&D's procyclicality is positively related to stock price's procyclicality (Figure 3, Page 1139). Since stock prices reflect the present discounted value of future production, highly pro-cyclical stock price suggests expected future production displays a stronger

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[13] As discussed in Section 2, panel unit-root test results suggest industry real value added contains a unit root in log levels but are stationary in log first differences.

correlation with current production. While the positive and significant estimates on the coefficient of $\widehat{\rho}_\iota \Delta lnY_{it}$ are consistent with the null, the estimated coefficients on ΔlnY_{it} are both, although negative, statistically insignificant. Put intuitively, controlling for persistence alone, just like controlling for finance alone, fails to generate counter-cyclical patterns of R&D implied by the Schumpeterian view.

We proceed by exploring whether controlling for both persistence and finance can uncover cyclical pattern of R&D. In particular, we add $\widehat{\rho}_\iota \Delta lnY_{it}$ to (4) as an additional control:

$$(12)\Delta lnR_{it} = \alpha_i + \beta\Delta lnY_{it} + \lambda\widehat{\rho}_\iota\Delta lnY_{it} + \theta_1\Delta lnQ_{it}^1 + \theta_2\Delta lnQ_{it}^2 + \varphi_1 N_i\Delta lnY_{it} + \varphi_2 L_i\Delta lnY_{it} + \gamma X_t + \varepsilon_{it}$$

The followings are true under the null. Firstly, R&D is concentrated when the present production is low and when the future production is high as long as the liquidity constraints do not bind: $\beta<0$, $\lambda>0$. Secondly, with binding constraints, R&D co-moves positively with net-worth growth or liquid-asset growth: $\theta_1 > 0$, $\theta_2 > 0$. Thirdly, industries with higher liquid-asset ratio or net-worth ratio feature more counter-cyclical or less pro-cyclical R&D: $\varphi_1 < 0$, and $\varphi_2 < 0$. Again, we estimate (12) with and without Petroleum Refining. The results are summarized in Panel B of Table 4.

Panel B of Table 4 reports the two estimates on λ with or without Petroleum Refining are both positive and statistically significant at the 1% level. Moreover, the estimates on θ_1, φ_1, θ_2, and φ_2 are very similar to those estimated based on (4) without controlling for cyclical persistence (as reported in Panel B of Table 3). Most interestingly, in Panel B of Table 4 the estimated output coefficients are both negative and statistically significant at the 5% level. According to the point estimates, a 10% increase in output growth is associated with 3.82% decrease in R&D growth for the 15-industry panel, and with a 5.67% decrease in R&D growth for the 16-industry panel. Such negative partial relationship between

R&D and contemporaneous output is consistent with the Schumpeterian view. These results reported in Table 4 suggest that the Schumpeterian view does capture important aspects of the cyclical patterns of innovation, but other factors such as liquidity constraint and output persistence masks firms' tendency to concentrate R&D during downturns, causing data to appear inconsistent with the Schumpeterian view.

An important note should be made before we conclude. We were motivated by the fact that the Compustat dataset, on which Barlevy (2007)'s finding that firm finance has no impact on R&D's cyclicality is based, covers publically traded firms only that are usually large in size and presumably less constrained financially. However, Barlevy (2007) compares the cyclicality of aggregate R&D reported by the NSF and that reported by the Compustat firms, and finds the latter is in fact even more pro-cyclical. This

5. Concluding Remarks

Based on an industry panel of R&D, production, and finance, we investigate liquidity constraint as an explanation for why the R&D data often appears inconsistent with the Schumpeterian view. Cross-section evidence shows Petroleum Refining possesses the highest net-worth ratio as well as counter-cyclical R&D. Panel evidence suggests average pro-cyclical R&D reflects cyclical variations in net-worth growth. Moreover, we find controlling additionally for output persistence helps to uncover cyclical patterns in R&D that are indeed consistent with the Schumpeterian view.

Several new messages can be taken away from this paper and point to directions for future research. First, we find evidence implying the impact of liquidity constraint on the cyclical patterns of R&D is also present for the U.S., as Aghion et al. (2005) documents for OECD countries. However, this is true only when industry finance is approximated using net-worth value, not when it is measured by liquid-asset value. Why does net worth better capture financial factors influencing R&D's cyclicality? Is R&D financed mainly through external borrowing in reality? Interpretation should be made with caution here as, for example, high net-worth value may reflect less debt rather than more borrowing. [14] Specific factors in corporate finance causing R&D growth to track net-worth growth should be explored in future research.

Second, liquidity constraint cannot be the only factor influencing R&D's cyclicality, as uncovering counter-cyclical R&D requires controlling for additional factors. This implies cyclical patterns in innovation should be much more complicated than the Schumpeterian view suggests. Many additional factors must be considered, including dynamic externality proposed by Barlevy (2007), complicacy in innovation process modeled by Francois and Lloyd-Ellis (2009), and output persistence explored in more details by Ouyang (2011a). The quantitative importance of various factors in influencing the cyclicality of R&D should be examined in future research.

Last but not the least, in reality the impact of liquidity constraint on innovation's cyclicality may be quantitatively more important than our results suggest. The NSF R&D database is still biased toward larger companies that tend to be less constraint financially. Moreover, the NSF R&D data is heavily

[14] Hall and Lerner (2009) review evidence on the relationship between cash flow and R&D growth and argue debt should be a disfavored source of financing R&D.

biased toward the manufacturing sector.[15] Starting from 2007, the NSF revised the R&D survey by putting more emphasis on non-manufacturing R&D and R&D carried overseas. Improved R&D data should be investigated by future research.

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[15] Non-manufacturing R&D may feature cyclical patterns different from those of manufacturing R&D. For example, Barlevy (2007) reports counter-cyclical R&D by the mining sector (Figure 3, page 1139).

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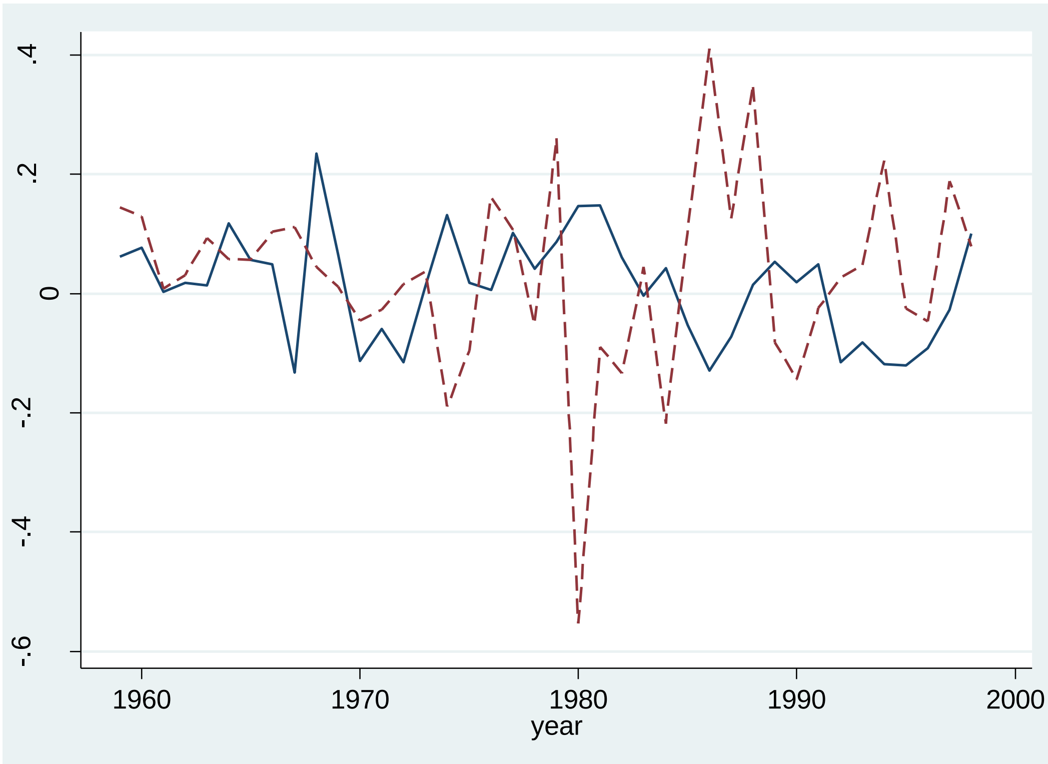
Figure 1: The Cyclicality of Petroleum Refining R&D



Note: The R&D growth and output growth for Petroleum Refining (SIC 29) from 1958 to 1998. The solid line indicates output growth and the dashed line indicates R&D growth. R&D is measured as R&D spending deflated by the GDP deflator; output is measured as the real value added. Data on R&D are from the NSF and data on output are from the NBER Manufacturing Productivity databases. See text for details.

Table 1: Industry R&D

Industry	Corr (Y_i, Y_A)	Corr (R_i, Y_i)	Without Controls	With Controls
Food (SIC 20, 21)	-0.0289	0.0741	0.1499 (0.2452)	0.0269 (0.3123)
Lumber (SIC 24, 25)	0.7151	0.0193	0.0764 (.3088)	-0.1131 (.3293)
Paper (SIC 26)	0.6435	-0.0787	-0.1785 (.3959)	-0.1932 (.4568)
Industrial Chemicals (SIC 281-2, 286)	0.7625	-0.1069	-0.0775 (0.1161)	-0.063 (0.1141)
Drugs (SIC 283)	0.3030	0.2243	0.2992 (0.2010)	0.3230 (0.2537)
Other chemicals (SIC 284-5, 287-9)	0.6334	-0.1501	-0.3515 (0.5376)	-0.2985 (0.4503)
Petroleum Refining (SIC 29)	0.4159	-0.3144	-0.1743*** (.0621)	-0.1264** (0.0524)
Rubber (SIC 30)	0.7361	0.1866	0.3384** (0.1664)	0.3185* (0.1691)
Stone (SIC 32)	0.8467	0.3208	0.6298** (0.2565)	0.6425** (0.2544)
Furrous Metals (SIC 331-32, 3398-99)	0.7627	0.0327	0.0355 (0.1513)	0.0188 (0.1181)
Non-ferrous metals (SIC 333-336)	0.7799	-0.0690	-0.0974 (0.2101)	-0.0050 (0.2042)
Metal Prods. (SIC 34)	0.8216	0.1050	0.1743 (0.2325)	0.0142 (0.2035)
Machinery (SIC 35)	0.6273	0.1627	0.2214 (0.2035)	0.5022** (0.2035)
Electronics (SIC 36)	0.5122	0.5638	0.4143*** (0.0643)	0.2721*** (0.0777)
Aerospace (SIC 372,376)	0.3450	0.3736	0.5197*** (0.2866)	0.6917*** (0.2075)
Instruments (SIC 38)	0.6331	0.2771	0.2884* (0.1687)	0.1255 (0.2272)
Pooled Sample	0.5527	0.0818	0.0854	0.0879

Note: R_i is the growth in industry R&D expenditure deflated by the GDP deflator; Y_i is the growth in industry real value added. Corr(Y_i ,Y_A) is the time-series correlation coefficient between Y_i and real GDP growth; Corr (R_i, Y_i) is that between R_i and Y_i. Output coefficient without controls is the OLS estimated coefficient on Yi by regressing R_i on a constant and Y_i. Output coefficient with controls is the OLS estimated coefficient on Y_i with a quadratic time trend allowed to differ before and after 1980 and a post-1992 dummy as additional controls. Robust standard errors are in parentheses. *** indicates significance at the 1% level; **significance at the 5% level; *significance at the 10% level. See text for details.

Table 2: Industry Financial Strength

Industry	Net-worth Ratio	Liquid-asset Ratio
Food (SIC 20, 21)	0.3435	0.0398
Lumber (SIC 24, 25)	0.1832	0.0289
Paper (SIC 26)	0.5780	0.0397
Industrial Chemicals (SIC 281-2, 286)	0.7099	0.0491
Drugs (SIC 283)	**1.4314**	**0.1983**
Other chemicals (SIC 284-5, 287-9)	0.6338	0.0887
Petroleum Refining (SIC 29)	**1.5799**	**0.1270**
Rubber (SIC 30)	0.3820	0.0384
Stone (SIC 32)	0.6080	0.0705
Furrous Metals (SIC 331-32, 3398-99)	0.5103	0.0767
Non-ferrous metals (SIC 333-336)	0.6412	0.0509
Metal Prods. (SIC 34)	0.3683	0.0485
Machinery (SIC 35)	0.6208	0.0763
Electronics (SIC 36)	**1.2774**	**0.1423**
Aerospace (SIC 372,376)	0.4218	0.0605
Instruments (SIC 38)	0.9114	0.0794
Cross-industry mean	0.7000	0.0759

Note: Industry Financial Strength. The net-worth ratio and the liquid-asset ratio are the real net worth and real liquid asset divided by real production value. Real net worth is measured as the 1958- 1998 quarterly average value of industry net worth in 2000 dollars. The real liquid asset is that of liquid assets in 2000 dollars. Real production value equals the sum of value added deflated by the value-of-shipment deflator and material cost deflated by the material-cost deflator. Top three values of each indicator are in bold. Data on net worth and liquid assets are from the Quarterly Financial Report by the Census Bureau. Data on nominal value added, nominal material cost, value of shipment deflator, material cost deflator are from the NBER Manufacturing Productivity Databases. See text for details.

Table 3: R&D and Finance

$$(3)\Delta lnR_{it} = \alpha_i + \beta \Delta lnY_{it} + \gamma X_t + \varepsilon_{it}$$

$$(4)\Delta lnR_{it} = \alpha_i + \beta \Delta lnY_{it} + \theta_1 \Delta lnQ_{it}^1 + \theta_2 \Delta lnQ_{it}^2 + \varphi_1 N_i \Delta lnY_{it} + \varphi_2 L_i \Delta lnY_{it} + \gamma X_t + \varepsilon_{it}$$

	Full Sample (640 obs)	No Petroleum Refining (600 obs)
Panel A: (3) Baseline Cyclicality		
ΔlnY_{it}	0.0879 (0.0760)	0.1524** (0.0699)
R-sq	0.0633	0.0628
F-stats	13.84	14.28
Panel B: (4) Cyclicality Controlling for Finance		
ΔlnY_{it}	0.0695 (0.1074)	0.0187 (0.1388)
ΔlnQ_{it}^1	0.0101** (0.0046)	0.0182** (0.0066)
ΔlnQ_{it}^2	0.0067 (0.0216)	0.0049 (0.0241)
$N_i \Delta lnY_{it}$	-0.6123** (0.2555)	-0.3739 (0.4228)
$L_i \Delta lnY_{it}$	6.4695* (3.1480)	5.1252 (3.4836)
R-sq	0.1547	0.1526
F-stats	13.14	13.92

Note: All regressions employ quadratic time trends allowed to differ before and after 1980 and a post 1992 dummy as additional controls indicated as X_t. Robust standard errors are in parentheses. *** indicates significance at the 1% level; **significance at the 5% level; *significance at the 10% level. See note to Table 1 for data sources; see note to Table 2 for financial indicators; see text for details.

Table 4: R&D, Persistence, and Finance

$$(11)\Delta lnR_{it} = \alpha_i + \beta\Delta lnY_{it} + \lambda\widehat{\rho_i}\Delta lnY_{it} + \gamma X_t + \varepsilon_{it}$$

$$(12)\Delta lnR_{it} = \alpha_i + \beta\Delta lnY_{it} + \lambda\widehat{\rho_i}\Delta lnY_{it} + \theta_1\Delta lnQ_{it}^1 + \theta_2\Delta lnQ_{it}^2 + \varphi_1 N_i\Delta lnY_{it} + \varphi_2 L_i\Delta lnY_{it} + \gamma X_t + \varepsilon_{it}$$

	Full Sample (640 obs)	No Petroleum Refining (600 obs)
Panel A: (11) Cyclicality Controlling for Persistence		
ΔlnY_{it}	-0.0980 (0.0661)	-0.0521 (0.0906)
$\widehat{\rho_i}\Delta lnY_{it}$	1.1809*** (0.3195)	1.0564*** (0.3624)
R-sq	0.1614	0.1599
F-stats	13.84	14.28
Panel B: (12) Cyclicality Controlling for both Persistence and Finance		
ΔlnY_{it}	-0.3818** (0.1528)	-0.5671*** (0.1624)
$\widehat{\rho_i}\Delta lnY_{it}$	1.1445*** (0.4137)	1.1551*** (0.4124)
ΔlnQ_{it}^1	0.0010** (0.0050)	0.0186** (0.0067)
ΔlnQ_{it}^2	0.0145 (0.0232)	0.0144 (0.0258)
$N_i\Delta lnY_{it}$	-0.4669*** (0.2125)	0.0233 (0.2684)
$L_i\Delta lnY_{it}$	4.9450* (2.6282)	2.0982 (2.2715)
R-sq	0.1649	0.1629
F-stats	12.99	13.98

Note: All regressions employ quadratic time trends allowed to differ before and after 1980 and a post 1992 dummy as additional controls indicated as X_t. $\widehat{\rho_i}$ is the estimated persistence as the AR(1) coefficient of industry output growth based on (9). Robust standard errors are in parentheses. *** indicates significance at the 1% level; **significance at the 5% level; *significance at the 10% level. See note to Table 1 for data sources; see note to Table 2 for financial indicators; see text for details.