working paper

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On the Cyclicality of R&D: Disaggregated Evidence

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FEDERAL RESERVE BANK OF CLEVELAND

Working Paper 07-07 June 2007

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This paper explores the link between short-run cycles and long-run growth by examining the cyclical properties of R&D at the disaggregated industry level. The relationship between R&D and output is estimated using an annual panel of 20 U.S. manufacturing industries from 1958 to 1998. The results indicate that R&D is in fact procyclical; but interestingly, estimates using demand-shift instruments suggest that it responds asymmetrically to demand shocks. We discuss the possibilities that liquidity constraints and technology improvement cause the observed procyclicality of R&D.

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

JEL codes: E22, E32.

Min Ouyang is an assistant professor at the University of California at Irvine and a research associate of the Federal Reserve Bank of Cleveland. She thanks Wayne Gray and Randy Becker for their kindly providing the extended NBER manufacturing productivity databases, and Stephanie Yang for research assistance. Linda Cohen, David Neumark, Amihai Glazer, Peter Rupert, Carl Walsh, Randy Wright provided helpful discussions. Detailed comments from David Neumark and Randy Wright are appreciated.

Introduction

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

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

This paper revisits the empirical evidence on the cyclicality of R&D, and hence on the opportunity-cost hypothesis. In particular, it examines the cyclical properties of R&D activities

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

at the industry level, rather than in the aggregate, by estimating the relationship between R&D and output using an annual panel of 20 U.S. manufacturing industries from 1958 to 1998. This provides far more observations on the relationship between output and R&D, and avoids potential aggregation bias. The idea is to take advantage of the fact that industrial cycles are not fully synchronized with aggregate fluctuations.

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

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

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

Data

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

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

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

1996, and recently extended to 2002. The MP data are aggregated to industries at the two-digit/three-and-a-half-digit level as defined in the R&D series. Output is measured as real value added, which equals the deflated value added using shipment-value-weighted price deflator. The results remain similar when output is measured as deflated value of shipments. This gives us an annual panel of R&D and output by 20 manufacturing industries covering 1958 through 1998.

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

Descriptive Statistics

To facilitate our empirical investigation at the disaggregated industry level, we compare industry-level volatility of R&D and output with that at the aggregate level. During our sample period of 1958-1998, the annual growth rate of U.S. real GDP averages 3% with a standard deviation of 2.2%; the annual growth rate of aggregate company-financed real R&D expenditures averages 5% with a standard deviation of 3.5%. Table 1 summarizes the sample means and the sample standard deviations of industry-level R&D growth and output growth.

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

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

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

Is R&D Concentrated When Production is Low?

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

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

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 is λ, which is allowed to differ before 1980s and afterward to capture the burst in innovation since the 1980s. When (1) is estimated using OLS, the estimates of *B(L)* represent the partial correlation between R&D growth and current or lagged output growth. While these partial correlations, in principle, may vary across industries, the common-slop coefficients on current and lagged output are imposed when estimating (1) to obtain sufficient degrees of freedom due to the short time series of annual data. Experimentations with different specifications of the model suggest that our results are robust to taking off the quadratic time trend, imposing common slopes of the quadratic time trend, allowing industry-specific time trend, including industry fixed effects, or replacing the time trend with year dummies. Results from regressions with lag lengths of zero, one year, and two years are summarized in Table 2. Standard errors accounting for within-industry heteroskedasticity and within-industry arbitrary serial correlation are reported in parentheses.

Table 2 confirms, from the disaggregated industry data, that R&D is *not* concentrated when production is low. The estimated relationship between R&D and contemporaneous output, as Column 1 shows, is positive and significant at the 10% level. In particular, a 10% increase in output is associated with a contemporaneous increase of 1.37% in R&D. According to Column 2 and Column 3, with lagged effects considered, a 10% increase in output is associated with a contemporaneous increase in R&D of 1.3%, a cumulative increase of about

2.0% in one year, and a cumulative increase of 3.0% in two years. Out of the six estimates, three are significant at 10% level, two are significant at 5% level, and one is significant at 1% level.

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

Can the Liquidity Constraints Help the Opportunity-cost Hypothesis?

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

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

but when output increases, R&D moves in opposite direction as the opportunity-cost hypothesis suggests. Put differently, under the opportunity-cost hypothesis with liquidity constraints, the response of R&D to output should be asymmetric. [3]

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

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

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

Demand-shift Instruments

There can be another reason that the data are inconsistent with the opportunity-cost hypothesis: this hypothesis only captures the response of R&D to demand shocks, which have no direct impact on R&D and therefore affect R&D only *indirectly* through their impact on the

[3] 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.

profitability of 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. This may explain why data does not support the opportunity-cost hypothesis.

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. While finding good instruments that are both exogenous and relevant to industrial output is difficult in practice, some studies (e.g. Ramey (1991) and Shea (1993)) use aggregate output as demand-shift instruments for disaggregate industries. This approach is implemented here by re-estimating equation (1) and equation (2) using two measures for aggregate output – real GDP and the Industrial Production Index – to instrument for industrial output. The two-stage least square estimations treat output as endogenous and employ current value, one lead, and one *more* lag of the instruments. The lengths of lead and lag are chosen so that each output term has at least one instrument lead and instrument lag. Therefore, the IV estimates of the coefficients on output in equation (1) and equation (2) reflect the response of R&D to output changes attributable to aggregate demand shocks approximated as aggregate output.[4]

The results are summarized in Table 3. Panel A of Table 3 presents the results with real GDP growth as the demand-shift instrument. The IV estimates of equation (1), summarized in the first three columns, are consistent with the OLS estimates: R&D responds positively to demand-driven changes in output. However, the estimates of equation (2), summarized in the fourth column, show that such positive responses mainly comes that R&D and output decline together in response to a negative demand shock (that causes output to decline). More

[4] Not surprisingly, all the first-stage estimations reveal significant positive correlation between industry output and the instruments. Detailed results are available upon requests.

specifically, in response to a demand shock that causes output to decline by 10%, R&D declines by 6.68%, significant at the 5% level. However, contrary to the OLS estimates, in response to a demand shock that *raises* output by 10%, R&D *declines* by 7.99%, significant at 10% level. Panel B of Table 3 shows that using industrial production index as demand-shift instrument returns similar results. The F-tests suggest that, for both instruments, one can reject $\beta_1 = \beta_2$.

The estimated asymmetric responses of R&D and output to demand shocks summarized in Table 3 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 the decrease in firms' net-worth and therefore tighter liquidity constraints. Therefore, R&D declines *always* in response to demand fluctuations. These results do not imply that R&D never increases, since they only capture R&D's response to demand shocks. As a matter of fact, the estimated correlation of R&D with an increase in output from OLS, as Table 2 shows, is positive, which suggests that other shocks are causing R&D and output to increase together.

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

Discussion

While the results from the IV estimates are consistent with the opportunity-cost hypothesis, one must point out, as a cautionary note, that 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. Apparently, aggregate output is relevant but cannot be exogenous enough, especially if a large part of aggregate output fluctuations reflects common technology shocks that can have a direct impact on industrial R&D. Shea (1993a, 1993b) proposes an input-output approach for IV selection that uses the downstream industrial output as the demand-shift instrument for upstream industry. But Shea also points out that the industries that possess good input-output instruments that pass both the relevance test and the exogeneity test are mostly at the three-digit and four-digit SIC level. Given that R&D data are mostly at two-digit level, this suggests difficulty in implementing the input-output approach to identify the impact of demand shocks on the cyclicality of R&D.

Nonetheless, the estimated negative response of R&D to positive demand shocks does support the opportunity-cost hypothesis, consistent with the “virtues of bad times” proposed by Aghion and Saint-Paul (1998). Unfortunately, R&D responds differently to negative demand shocks, so that such potential virtues are not realized. And we have suggested liquidity constraints as an explanation. As a result, demand fluctuations cause R&D to decline regardless of their impact on output. It may seem natural to conclude from here that counter-cyclical fiscal policy, which aims to smooth out short-run demand fluctuations, is desirable. However, one should remain cautious in drawing such a conclusion, given the difficulty of identifying the sources of fluctuations in reality and the possibility that fiscal policy can itself be the source of demand fluctuations.[5]

Conclusion

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

Future empirical research on the cyclical properties of R&D should focus on the search of better demand-shift instruments to separate the impact of demand shocks from those of technology shocks, or on constructing R&D data at more detailed industry level (or even at the firm level). Future theoretical research should devise models exploring the combined impact of liquidity constraints, demand shocks, and technology shocks on the cyclical properties of innovative activities.

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

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

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

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

Table 2: Cyclical R&D and Liquidity Constraints: Evidence from OLS

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

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

	OLS1	**OLS2**	**OLS3**	**OLS4**	
	Y	Y	Y	$Y_{it} D_{it}^H$	$Y_{it} D_{it}^L$
Contemp.	0.1377 (0.0700)*	0.1272 (0.0664)*	0.1360 (0.0669)*	0.1357 (0.1053)	0.1395 (0.0657)**
Cumulatively in one year	-	0.2060 (0.0831)**	0.1953 (0.0813)**	-	-
Cumulatively in two years	-	-	0.2963 (0.0800)***	-	-
No. of obs.	794	774	754	355 for *dummyH*=1	439 for *dummyL*=1
F-test $\beta_1 = \beta_2$	-	-	-	0.00 (*p*=0.9707)	
R-squared	0.0350	0.0369	0.0392	0.0350	

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

Table 3: Cyclical R&D and Liquidity Constraints: Evidence from IVs

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

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

	IV1	**IV2**	**IV3**	**IV4**	
No. of obs.	794	774	754	355 for D^H=1	439 for D^L=1
Panel A: Real GDP as IV					
	Y	Y	Y	YD^H	YD^L
Contemp.	0.1627 (0.0833)*	0.1586 (0.0921)*	0.1860 (0.0937)*	-0.7995 (0.4107)*	0.6681 (0.2412)**
Cumulatively in one year	-	0.2348 (0.1139)*	0.2362 (0.1113)**	-	-
Cumulatively in two years	-	-	0.3182 (0.1227)**	-	-
F-test $\beta_1 = \beta_2$	-	-	-	5.58 (*p=0.0289*)	
Panel B: Industrial Production as IV					
	Y	Y	Y	YD^H	YD^L
Contemp.	0.1206 (0.0739)	0.1230 (0.0821)	0.1678 (0.0911)*	-0.5893 (0.3392)*	0.5448 (0.2026)**
Cumulatively in one year	-	0.1939 (0.0916)**	0.2085 (0.0910)**	-	-
Cumulatively in two years	-	-	0.3232 (0.1205)**	-	-
F-test $\beta_1 = \beta_2$				4.92 (*p=0.0389*)	

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

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