Cyclical Persistence and the Cyclicality of R&D

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Abstract

We propose cyclical persistence as an important factor influencing the timing of innovation. Schumpeter (1939) argues innovation should be concentrated during recessions when its marginal opportunity cost as forgone output is low. We propose the timing of innovation should be affected additionally by the cyclicality of innovation's marginal expected return. A simple theory is presented, showing higher persistence can drive R&D pro-cyclical by raising the cyclical response of innovation's marginal expected return to dominate the response of innovation's marginal opportunity cost. We carry the theory to an industry panel of R&D and output. Our estimation results suggest persistence helps to account for the observed cross-industry differences in R&D's cyclicality.

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1 Introduction

Short-run cycles and long-run growth have long been recognized as a unified phenomenon. For example, Ramey and Ramey (1995) document a negative relationship between volatility and growth across 92 countries, suggesting studying the two separately can be missing an important linkage. While this linkage can arise through various channels, recently many authors have explored the innovation channel by examining R&D (Bloom, 2007). On this matter, an opportunity cost (hereafter OC) view has been proposed in the spirit of Schumpeter (1939): innovation should be concentrated during recessions when their marginal opportunity cost in terms of forgone output is low (e.g., Aghion and Saint-Paul, 1998). Unfortunately, data shows R&D is procyclical both at the aggregate level and at the industry level (e.g., Fatas, 2000; Ouyang, 2010). This has motivated some researchers to question the validity of Schumpeterian timing of innovation, and some others to argue Schumpeterian timing of R&D is distorted by factors such as liquidity constraints (Barlevy, 2007; Francois and Lloyd-Ellis, 2009; Aghion et al., 2005; Ouyang, 2010).

This paper proposes *cyclical persistence* as an additional factor influencing the timing of innovation. We argue the original Schumpeterian theory highlights variations in innovation's marginal opportunity cost, but variations in the marginal expected return to innovation also matter. We incorporate into a simple two-period model the following idea: the timing of innovation depends on the cyclicality of two elements – innovation's marginal opportunity cost and its marginal expected return; during recessions, its marginal opportunity cost and its marginal expected return both decline, so that whether innovation rises depends on whose cyclicality dominates.

We thus highlight cyclical persistence as an additional factor determining the timing of innovation. In particular, higher persistence implies a larger component of present shocks will be carried into the future, so that the expected future return to present innovation becomes more responsive to present shocks. Our model predicts higher persistence makes it more difficult for cyclical responses in innovation's marginal opportunity cost to dominate, so that R&D is more likely to appear pro-cyclical. Carrying the theory to an industry panel of output and R&D suggests cyclical persistence, measured in various ways, contributes to the cross-industry differences in R&D's cyclicality. Moreover, we find the impact of persistence and liquidity constraints are both present.

Previous authors have noticed the importance of cyclical persistence on the linkage between cycles and growth. Aghion and Saint-Paul (1998) argue the Schumpeterian timing of innovation fails to hold with permanent shocks. Saint-Paul (1993) finds the negative impact of higher demand on productivity appears stronger when fluctuations are more transitory. Fatas (2000) proposes pro-cyclical innovation can cause persistence and documents a positive cross-country relationship between growth rates and persistence. Fatas (2000)'s evidence does not contradict ours, as the causality can indeed go both ways to generate that relationship. Nonetheless, neither Saint-Paul (1993) nor Fatas (2000) empirically identify the channels through which persistence matters: Saint-Paul (1993) estimates the response of R&D to demand shocks to be statistically insignificant; Fatas (2000) does not examine any data on innovation. By contrast, we examine specifically the channel of innovation, and find cyclical persistence has significant impact on R&D's cyclicality. Our results stay robust to controlling for the impact of R&D intensity on persistence (as Fatas(2000) proposes), to employing the instrumental-variable estimation approach, and to controlling for the presence of liquidity constraints.

The rest of the paper is organized as follows. Section 2 presents the theory. Section 3 carries the theory to data. Section 4 concludes.

2 The Model

The economy is populated by over-lapping generations of entrepreneurs who live for two periods. There are L entrepreneurs in each generation. Each period, young entrepreneurs produce and innovate; old entrepreneurs adopt the productivity gain from the last-period innovation, produce, and die. Productivity gain is transferred between generations at no cost. Each entrepreneur is endowed with a fixed amount of labor normalized as one. Let E to be the production labor and R to be the innovation labor: $E + R = 1$ for young entrepreneurs; and $E = 1$ for old entrepreneurs.

2.1 Production and Innovation

Output produced by an young entrepreneur, denoted Y_y, is determined by A, an endogenous productivity copied from old generation at no cost, and production labor E :

$$Y_y = A\varepsilon E^{\alpha}, \quad 0 < \alpha < 1. \tag{1}$$

ε is a cyclical shock that follows a Markov process with support $\left[\varepsilon^l, \varepsilon^h\right] \subseteq \mathbb{R}_+$, where $0 < \varepsilon^l < 1$, $\varepsilon^h > 1$. ε has an unconditional mean normalized to one and a conditional mean $E_t\left(\varepsilon_{t+1}|\varepsilon_t\right) = \varepsilon_t^{\rho}$, where $-1 < \rho < 1$ captures the persistence. The key assumption on ε is it directly impacts production only, and indirectly affects innovation by influencing innovation's opportunity cost.[1] Higher ε raises output as well as the marginal product of labor, so that the marginal forgone output as the opportunity cost of innovation also rises.

The endogenous productivity A has the following structure:

$$A = \gamma^m, \gamma > 1 \tag{2}$$

m is an integer that denotes the technology generation. Entrepreneurs can advance to higher-generation technology by engaging in innovation. In particular, R units of innovation labor generates a probability of ϕR of discovering technology generation $m + 1$, which raises A to γA. ϕ is a parameter smaller than one that captures the productivity of innovation labor.

[1]Ouyang (2010) proposes technology shocks can have direct impact on innovation. For example, in response to the arrival of new technology, firms increase R&D spending at the purpose of developing new technology into further productivity gain. In this paper, we analyze the impact of production shocks on innovation only following theories studying the Schumpeterian timing of innovation (Barlevy, 2007; Aghion, et al., 2005).

Following Barlevy (2007), we assume ϕ stays constant over time, based on Griliches (1990)'s documentation of acyclical productivity in the innovation sector.

Once higher generation of technology is discovered with successful innovation, it requires an additional cost Ac with $c > 0$, to adopt new technology into period-two production. This adoption cost occurs at the end of period one or at the beginning of period two. The adoption cost is normalized by A, as more advanced technology can be costlier to adopt. Let Y_o to be the output of an old entrepreneur who copied A form his predecessor, invested R into innovation when he was young, and now puts all his labor into production. His output is $Y_o = \gamma A\varepsilon$ if innovation and adoption are both successful, and is $Y_o = A\varepsilon$ otherwise. It is assumed that, for any $R \in (0, 1]$ and $\varepsilon \in \left[\varepsilon^l, \varepsilon^h\right]$, $\frac{(\gamma-1)\varepsilon^\rho}{1+r} > c$, so that an old entrepreneur always chooses to adopt the new generation of technology.

The adoption cost c is a key element of our model. c is assumed independent of production shocks. One can think of c as reflecting the cost of overhead labor whose wage stays relatively rigid over the business cycle. As explained later, this assumption is critical to break up the linear relationship in the conventional OC models between innovation's marginal expected return and the expected cyclical shocks. In spirit, c is very similar to the fixed operation cost modeled by Barlevy (2007).[2] This adoption cost is also present in the model by Aghion et al. (2005) at the purpose of introducing liquidity constraints. They assume an imperfect financial market to analyze how entrepreneurs' ability to finance c varies over the business cycle. Since our focus is cyclical persistence, we deviate from financial market frictions by assuming a perfect financial market in which an old entrepreneur has no difficulty financing Ac either through internal financing or external borrowing.

Under this setup, innovation raises future productivity, but requires sacrifice of present production. Young entrepreneurs choose R to balance this trade-off.

[2] In our model, entrepreneurs pays c only if innovation is successful. In the model by Barlevy (2007), the operation cost c is paid by entrepreneurs with leading technology only. Therefore, in both models this cost is paid with probability of ϕR. As a result, c enters the first-order conditions but remains independent of cyclical shocks.

2.2 Marginal Opportunity cost and Marginal Expected Return

Once innovation is successful, an old entrepreneur adopts higher generation of technology by paying Ac before he produces in period two. Let r to indicate the interest rate. Suppose price equals one and there is no inflation. Let V to be the present discounted value of an entrepreneur's life-time profit. Throughout the rest of the paper, we normalize A as one. Hence, a forward-looking young entrepreneur optimizes as follows:

$$\underset{R}{Max} \quad V(R,\varepsilon) = \varepsilon(1-R)^{\alpha} + (1-\phi R)\frac{\varepsilon^{\rho}}{(1+r)} + \phi R\left[\frac{\gamma\varepsilon^{\rho}}{(1+r)} - c\right] \tag{3}$$

Note c is not discounted by $\frac{1}{1+r}$ because it occurs before period-two production takes place. V is concave in R with $V_{RR} < 0$, and $V_R(1,\varepsilon)$ is negative. We further assume $V_R(0,\varepsilon) = \frac{\phi(\gamma-1)}{1+r}\varepsilon^{\rho} - \phi c - \alpha\varepsilon > 0$ for any ε to ensure an interior solution. The first-order condition with respect to R, $V_R(R,\varepsilon) = 0$, gives:

$$\varepsilon\alpha(1-R^{*})^{\alpha-1} = \frac{\phi\,(\gamma-1)}{1+r}\varepsilon^{\rho} - \phi c, \tag{4}$$

The left-hand side of (4) captures the marginal opportunity cost of innovation as forgone present output. The right-hand side is the marginal expected net return to innovation. (4) suggests optimal R, denoted as R^{*}, balances the trade-off between present and future return, equating the marginal opportunity cost to the marginal expected return. Because c is independent of production shocks, the marginal opportunity cost of innovation is linear in ε, but the marginal expected return to innovation is not linear in ε^{ρ}.

While a closed-form solution for R^{*} can be derived from (4), here we differentiate (4) with respect to R^{*} and ε based on the implicit function theorem. The purpose is to explore how the the cyclicality of the marginal opportunity cost of innovation, captured by the left hand side of (4), relative to that of the marginal expected return to innovation, reflected by the right-hand side of (4), determine the cyclical responses of R^*:

$$\frac{dR^*}{d\varepsilon} = \frac{\frac{\phi(\gamma-1)}{1+r}\rho\varepsilon^{\rho-1} - \alpha(1-R^*)^{\alpha-1}}{(1-\alpha)\,\alpha\varepsilon(1-R^*)^{\alpha-2}}. \tag{5}$$

(5) suggests the sign of $\frac{dR^*}{d\varepsilon}$ is determined by the magnitude of $\alpha(1-R^*)^{\alpha-1}$, as ε's impact on the marginal opportunity cost, relative to that of $\frac{\phi(\gamma-1)}{1+r}\rho\varepsilon^{\rho-1}$, as ε's influence on the marginal expected return. Higher ε raises both, so that whether it encourages or discourages innovation depends on which effect dominates.

Proposition 1 *A positive production shock that raises output reduces innovation if and only if the cyclicality of innovation's marginal opportunity cost dominates that of its marginal expected return; in that case, innovation and production comove negatively over time.*

In other words, $\frac{dR^*}{d\varepsilon} < 0$ if and only if $\frac{\phi(\gamma-1)}{1+r}\rho\varepsilon^{\rho-1} < \alpha(1-R^*)^{\alpha-1}$. In this case, higher ε raises production but reduces innovation, and innovation is counter-cyclical. This is the case emphasized by the conventional OC theories. For example, Aghion and Saint-Paul (1998) model the marginal expected return to be reaped over the entire future, including periods with high profitability and those with low profitability, so that its cyclical response fails to dominate that of innovation's opportunity cost. Conversely, theories that propose factors other than OC stress the dominance of cyclicality in innovation's marginal expected return. For example, Barlevy (2007) argues the return to R&D is short-run rather than long-run due to dynamic externalities inherent to the R&D process, which amplifies the cyclicality of R&D's marginal return and therefore drives R&D pro-cyclical.

The case captured by Aghion and Saint-Paul (1998) is equivalent to the case in model when $c = 0$. Assuming $c = 0$, differentiating (4) again with respect to R^* and ε based on the implicit function theorem gives:

$$\frac{dR^*}{d\varepsilon} = \frac{-(1-\rho)}{(1-\alpha)\,\varepsilon(1-R^*)} \tag{6}$$

(6) is negative as long as $\rho < 1$. With $c = 0$, the marginal opportunity cost is linear in ε and the marginal expected return is linear in ε^ρ; therefore, the impact of ε on the former *must* dominate the latter as long as $\rho < 1$. Aghion and Saint-Paul (1998) establish this is the case as long as there is a positive probability for present shocks *not* to persist. Their argument arises from the modeling feature that the marginal opportunity cost and the marginal expected return are both linear in (expected) cyclical shocks.

However, there is no reason to believe that marginal opportunity cost and the marginal expected return are both linear in (expected) cyclical shocks. Barlevy (2007) models a fixed operation cost to break up such linearity. Caballero and Hammour (1994) provide an example for the cyclicality of the marginal opportunity cost to dominate without such linearity. They model the return to productivity growth embodied through entry, and its opportunity cost realized by exit; cyclical response in entry is dampened by an entry cost increasing in entry size, so that it fails to dominate the cyclical response in exit. In our model, such linearity is broken up by the adoption cost c, so that the cyclicality of marginal opportunity cost may dominate or may not.

2.3 Cyclical Persistence and Timing of Innovation

To examine the condition under which optimal innovation is counter-cyclical, (4) gives the closed-form solution for R^*:

$$R^* = 1 - \left(\frac{\phi}{\alpha}\right)^{\frac{1}{\alpha-1}} \left[\frac{(\gamma-1)}{(1+r)}\varepsilon^{\rho-1} - \frac{c}{\varepsilon}\right]^{\frac{1}{\alpha-1}} \tag{7}$$

Differentiating R^* with respect to ε shows that higher ε *reduces* R^* if and only if $(\gamma-1)(1-\rho)\varepsilon^\rho > c(1+r)$. In this case, ε's influence on the marginal opportunity cost of innovation equals $\frac{\phi(\gamma-1)}{1+r}\varepsilon^{\rho-1} - \frac{\phi c}{\varepsilon}$, and that on the marginal return equals $\frac{\phi(\gamma-1)}{1+r}\rho\varepsilon^{\rho-1}$. The former dominates the latter if and only if $(\gamma-1)(1-\rho)\varepsilon^\rho > c(1+r)$. Again, innovation is counter-cyclical if and only if the cyclicality of the opportunity cost dominates, consistent with

Proposition 1.

Now we examine how cyclical persistence affects the chance for this condition to hold. Apparently, higher ρ reduces $(\gamma-1)(1-\rho)\varepsilon^{\rho}$, and thus makes $(\gamma-1)(1-\rho)\varepsilon^{\rho} > c(1+r)$ less likely to hold, if and and only if $\ln(\varepsilon)(1-\rho) < 1$. To see this from another angle, define x to capture the magnitude of ε's impact on innovation's marginal opportunity cost relative to that on innovation's marginal expected return:

$$\begin{aligned} x &\equiv \alpha(1-R^{*})^{\alpha-1} - \frac{\phi(\gamma-1)}{1+r}\rho\varepsilon^{\rho-1}8 \\ &= \frac{\phi(\gamma-1)}{1+r}(1-\rho)\varepsilon^{\rho-1} - \frac{\phi c}{\varepsilon} \end{aligned} \tag{1}$$

Again, $\frac{dx}{d\rho} < 0$ if and only if $\ln(\varepsilon)(1-\rho) < 1$. Note that ρ influences both ε's impact on innovation's marginal opportunity cost and ε's impact on innovation's expected marginal return. At the optimum, ρ's influence on the former equals $\frac{\phi(\gamma-1)}{1+r}\varepsilon^{\rho-1}\ln\varepsilon$ and that on the latter equals $\frac{\phi(\gamma-1)}{1+r}\varepsilon^{\rho-1}(1+\rho\ln\varepsilon)$. Higher ρ raises the former less than the latter when $\frac{\phi(\gamma-1)}{1+r}\varepsilon^{\rho-1}\ln\varepsilon < \frac{\phi(\gamma-1)}{1+r}\varepsilon^{\rho-1}(1+\rho\ln\varepsilon)$, which suggests $\ln(\varepsilon)(1-\rho) < 1$.

Proposition 2 *With* $\ln(\varepsilon)(1-\rho) < 1$*, higher* ρ *reduces the magnitude of cyclical responses in innovation's marginal opportunity cost relative to that of the cyclical response of innovation's marginal return, so that it is less likely for innovation to respond negatively to production shocks.*

To see the value combinations of ε and ρ for $\ln(\varepsilon)(1-\rho) < 1$ to hold, Figure 1 plots, in the top panel, the value of $1-\ln(\varepsilon)(1-\rho)$ against $\ln\varepsilon \in [-1.5, 1.5]$ and $\rho \in [-1, 1]$.[3] It shows $\ln(\varepsilon)(1-\rho) > 1$ occurs when ρ is very low and when ε is very high. Panel 2 plots this value range in a $(\ln\varepsilon, \rho)$ space: they are located at the lower-right corner. In particular, $\ln(\varepsilon)(1-\rho) < 1$ *may* not hold only when $\ln\varepsilon > 0.5$ and $\rho < 0.3333$.

This section has presented a simple model, arguing persistence influences the timing of

[3]The value range of ε is set according to the observed output growth in an industry panel that will be examined in the next section.

innovation. Several remarks should be made. First, in the model production shock ε is assumed to be distributed continuously. But our analysis also applies to discrete production shocks. A sketch of the version of the model with discrete shocks are presented in the appendix.

Second, our results differ from Aghion and Saint-Paul (1998) in important ways. Aghion and Saint-Paul (1998) also consider the impact of persistence, arguing *permanent* recessions should have no growth effect.[4] In their model, higher ε has no impact on innovation with $\rho = 1$ and reduces innovation with $\rho < 1$; but, as long as $\rho < 1$, the value of ρ no longer matters. In our model, higher ε raises innovation with $\rho = 1$ and reduces innovation with $\rho = 0$; with $0 < \rho < 1$, the impact of ε on innovation may be positive or negative, and higher ρ makes it likely to be positive. This is because, as argued earlier, marginal opportunity cost and marginal return of innovation are both linear in (expected) cyclical shocks in the model of Aghion and Saint-Paul (1998), but such linearity is broken up by c in our model.

Third, our result does not hold against the argument by Aghion et al. (2005) that pro-cyclical R&D is driven by binding liquidity constraint. Persistence affects the optimal timing of innovation, while such timing can be *hindered* by binding liquidity constraints. As a matter of fact, persistence and liquidity constraint can work together in reality, driving R&D procyclical. The impact of persistence and liquidity constraint are both investigated in Section 3.

3 Industry Evidence

Our theory predicts, for reasonable values of persistence and production shocks, higher persistence makes innovation more likely to be concentrated when production is high instead of when production is low. We carry this theoretical prediction to an industry panel of production and R&D, examining whether cyclical persistence helps to explain the observed

[4] Aghion and Saint-Paul (1998) present two versions of their model. The first assumes that innovation competes with production for resources; the second assumes that innovation uses produced goods instead of production resources. It is the first version that captures the conventional opportunity-cost view.

variation in industry R&D's cyclicality.

In our theory, Propositions 1 and 2 capture innovation's response to production shocks. However, in practice shocks are hard to measure directly. One approach is to identify shocks employing a VAR estimation; but this approach relies heavily on the identification assumptions (Shea, 1998). Therefore, we follow Barlevy (2007) and Ouyang (2010) to examine the cyclicality of R&D as the comovement between R&D and output. The underlying assumption is positive production shocks impact output positively, so that R&D's comovement with output qualitatively resembles R&D's response to production shocks.[5]

3.1 Data

Our empirical investigation is based on a 1958-1998 panel of R&D and production of 20 manufacturing industries compiled by Ouyang (2010). These 20 manufacturing industries together account for 90.65% of the total company-financed R&D in the U.S.. R&D data is from the NSF, as 1958-1998 company-financed R&D expenditures for 20 U.S. manufacturing industries at the two-digit and the combination of three-digit level based on the 1987 Standard Industry Classification (SIC) system.[6] Production data for these 20 R&D industries is aggregated from the NBER Manufacturing Production (MP) database that provides 1958-2005 production data for manufacturing industries at the four-digit SIC level. Details on the sample design of the two data sets and interpolations of the missing observations are discussed by Ouyang (2010). The R&D series are converted into 2000 dollars using the

[5]One possibility is a higher production shock raises innovation so much that output declines in response to a positive production shock. But it unlikely that innovation's cyclical response is big enough to reverse the direct impact of production shocks on production. According to our industry panel, measured R&D is very small quantitatively: the annual real industry R&D spending averages 26.65 million in 2000 dollars, only about 0.95% of the average real investment of 3436.72 million dollars. Sufficiently small R makes it unlikely for the cyclical response of R to dominate that of output.

[6]The R&D-by-industry series is truncated by 1998 because, starting from 1999, R&D by industry is published based on the North American Industry Classification System (NAICS). The transformation between SIC and NAICS is not recommended by the NSF. To make the year-to-year comparison more convenient, the NSF transforms the 1997-1998 R&D-by-industry series under the SIC into those under the NAICS. Unfortunately, the concordance behind the transformation remains confidential. Moreover, it is claimed that "the estimates for 1997 and 1998 (after transformation) are not necessarily representative of the NAICS categories of industries in those years... as it may involve a large number of errors." (http://www.nsf.gov/statistics/srs01410/).

GDP deflator (Barlevy, 2007). Output is measured as real value added – the deflated value added using shipment-value-weighted price deflator. Measuring output as deflated value of shipments generates similar results on the cyclicality of R&D.

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

3.2 The Base-line Cyclicality of Industry R&D

Table 1 lists the 20 sample manufacturing industries in Column 1 together with their SIC codes in Column 2. Column 3 presents the time-series correlation coefficients between R&D growth and output growth for each industry. Out of the 20 coefficients, six are negative and 14 are positive. Pooling industries together gives an average correlation coefficient of 0.1047.

We run the following OLS regression, industry by industry, to estimate the cyclicality of industry R&D:

$$\triangle \ln R_{it} = \beta_{i0} + \beta_{i1} \triangle \ln Y_{it} + \gamma_i X_t + \epsilon_{it}. \tag{9}$$

$\triangle \ln R_t$ indicates the R&D growth in year t; $\triangle \ln Y_t$ is the output growth. The estimate on β_{i1} reflects how R&D growth co-moves with output growth for industry i. X_t is a set of control variables, including a quadratic time trend allowed to differ before and after 1980 as well as a post-1992 dummy following Ouyang (2010): the time trend is allowed to differ before and after 1980 to reflect a burst in innovation starting from the early 1980s; the post-1992 dummy is supposed to capture any potential impact of a change in the ISRD sample design starting from 1992. The sample size of each regression is 40. The results stay robust to including lagged output, as Ouyang (2010) reports the cumulative correlation of R&D growth and output growth are quantitatively similar to the contemporaneous correlation.

Column 4 of Table 1 summarizes the OLS estimation results of (9); robust standard errors are in parentheses. Seven out of the 20 estimates are negative, only one is statistically significant; 13 estimates are positive, five are statistically significant. Pooling industries together produces an estimate of 0.1351, significant at the 10% level. These results are also robust to dropping the time trends and the post-1992 dummy or replacing them by year dummies.

The conventional theory predicts R&D to be concentrated when output is low. The baseline cyclicality of industry R&D summarized in Columns 3-4 of Table 1 provides little support for such theory. Instead, it shows R&D is pro-cyclical on average and, most importantly, the cyclicality of R&D differs significantly across industries. For example, the estimated output coefficients that are statistically significant at the 10% level or above ranges from -0.1263 for Petroleum Refining that implies counter-cyclicality, to 0.6917 for Stones that suggests strong pro-cyclicality.

3.3 Persistence Measures

We measure cyclical persistence using data on output growth, assuming persistence in production shock ε is reflected as persistence in output over the production cycle driven by ε. In particular, we apply two persistence measures.

The first one follows Cochrane (1988) and Fatas (2000), measuring persistence as the four-year output variance ratio. In particular, cyclical persistence for industry i, denoted as ρ_i, is measured as:

$$\rho_i \equiv \frac{1}{J} \frac{var\left(\triangle \ln Y_{it} - \triangle \ln Y_{it-J}\right)}{var\left(\triangle \ln Y_{it} - \triangle \ln Y_{it-1}\right)}, \tag{10}$$

where $\triangle \ln Y_{it}$ is the output growth for industry i in year t, and var is the variance. We use $J = 4$, while the results are robust to other J values. According to Cochrane (1988), (10) is equivalent to a weighted sum of auto-correlations; it measures the extent to which annual output fluctuations are trend reverting.

The second persistence measure estimates the AR(1) coefficient on output growth, controlling for the potential impact of innovation on persistence proposed by Fatas (2000). Fatas (2000) argues the potential influence of procyclical innovation on cyclical persistence should be positively correlated with the intensiveness of growth activities (page 156). Following his argument, we estimate ρ_i for each industry, controlling for the intensiveness of growth activities approximated as the mean level of industry R&D:

$$\triangle \ln Y_{it} = \rho_i \triangle \ln Y_{it-1} + \zeta \ln R_i + \epsilon_t. \tag{11}$$

$\triangle \ln Y_{it}$ is the output growth of industry i in year t. $\ln R_i$ is the time-series average of log levels of real R&D spending. The estimate on ρ_i based on (13) captures the 1958-1998 average annual AR(1) persistence in output growth for industry i, controlling for the R&D level. We control for the intensiveness of growth activities using mean R&D level instead of lagged R&D growth, because the latter reduces the sample size and because it is hard to determine the appropriate lag length for past R&D to impact present production. The results stay robust to replacing the mean R&D level by mean R&D growth or by a constant. Due to the limited sample size of 40 observations for each industry, we estimate AR(1) coefficient only. Also, experimentation with different modeling specifications shows including output growth lagged by two years or more in (11) worsens the estimation fit.

Table 1 lists the measured Cochrane persistence in Column 5 and the estimated AR(1) persistence in Column 6. Both measures differ significantly across industries: the Cochrane persistence measure ranges from 0.1589 for Other Chemicals to 0.6236 for Scientific Instruments; the AR(1) persistence ranges from -0.0586 for Autos and Others to 0.5053 for Aerospace. The two measures are positively correlated with a correlation coefficient of 0.6859. The Cochrane measure averages 0.3121; the AR(1) measure averages 0.1858 and is significant at the 5% level.

As a comparison, Fatas (2000) applies the Cochrane measure of annual persistence to 120 countries and reports it ranges roughly between -0.5 and 2, stronger than our industry-level measure. This should not be surprising, because inter-industry comovement can cause aggregate output to display stronger persistence than industry output (Shea, 2002). Also note the Cochrane measures are in general higher than the AR(1) measures. This should not be surprising either, as the Cochrane measure does not control for potential influence of innovation on cyclical persistence (Fatas, 2000).

3.4 Preliminary cross-section evidence

We examine whether the cross-industry difference in cyclical persistence contributes to that in the baseline cyclicality of industry R&D. According to Proposition 2, higher persistence makes R&D more likely to appear pro-cyclical as long as $1 + \rho \ln \varepsilon > 0$.

Figure 1 shows $\ln(\varepsilon)(1-\rho) < 1$ does not hold only when ρ is very low and when $\ln \varepsilon$ is very high. We first evaluate whether our sample industries fall into that value range. According to Columns 5 and 6 of Table 1, both persistence measures stay within $[-1, 1]$. According to Figure 1, for $\rho \in [-1, 1]$, $\ln \varepsilon$ needs to exceed 0.55 for $1 - \ln(\varepsilon)(1-\rho)$ to occasionally fall below zero.

Since ε is not directly observable, we approximate $\ln \varepsilon$ using output data. In our theory, ε has an unconditional mean of one, suggesting $\ln \varepsilon$ fluctuates around zero. In our panel, log output does not have a zero mean due to the existence of a growing trend. Thus, we use output growth, as the difference-detrended log output, to approximate the value range for $\ln \varepsilon$. In our panel, annual industry output growth ranges from -0.55 to 0.48, suggesting $\ln \varepsilon$ fluctuates approximately within $[-0.5, 0.5]$. Therefore, we conclude $\ln(\varepsilon)(1-\rho) < 1$ holds so that Proposition 2 applies.

We proceed to examine whether R&D's cyclicality relates to cyclical persistence cross-section. Figure 2 plots, in the top two panels, the cyclicality of industry R&D as the estimated β_{i1} based on (9) against the two persistence measures. Each dot indicates a sample industry. In both panels, the two variables are positively correlated; the correlation coefficient equals 0.5234 for the Cochrane measure and 0.4433 for the AR(1) measure.

As a robustness check, the bottom two panels of Figure 2 repeat the plots, excluding outlier industries – those with the highest or the lowest persistence as well as those with the highest or the lowest estimate on β_{i1}. In particular, Aerospace is excluded from both panels, as the industry with the highest persistence either based on the Cochrane measure or the AR(1) measure *and* as the industry with the highest estimate on β_{i1}; Scientific Instruments is also taken out of both panels, as the industry with the lowest estimate on β_{i1}; Autos and Others is excluded from the left-bottom panel, as the industry with the lowest AR(1) measure; Drugs is taken out of the right-bottom panel, as the industry with the lowest Cochrane measure. The bottom two panels of Figure 1 shows, without these outlier industries, the positive correlation between the cyclicality of industry R&D and persistence becomes even stronger. The correlation coefficient equals 0.6152 in the left-bottom panel and 0.7035 for the right-bottom panel.

Table 2 reinforces the impression from Figure 2. It summarizes the OLS results of regressing $\widehat{\beta_1}$ on a constant and each of the persistence measures. The sample size is 20 for the full sample and 17 for the sample excluding the outlier industries. The four estimated coefficients on persistence are all positive and significant at the 10% level or above; excluding the outlier industries generates bigger point estimates, implying a stronger positive relationship. In summary, Figure 2 and Table 2 suggest industries with higher persistence display stronger comovement between R&D and output.

However, such relationship does not serve as a strict test of our theory. Proposition 2 argues R's response to ε rises in ρ, not that R's comovement coefficient with Y rises in ρ. Strictly speaking, our theory suggests higher ρ makes it more likely for R to co-move positively with Y. To examine how cyclical persistence affects the probability of industry R&D's being pro-cyclical, we estimate a linear probability model (LPM) and a probit model

:

$$P\left(pro_i = 1|\rho_i\right) = \alpha_0 + \alpha_1\rho_i + \epsilon_i 12 \quad (2)$$
$$P\left(pro_i = 1|\rho_i\right) = \Phi\left(\alpha_0 + \alpha_1\rho_i\right).$$

pro_i equals one for the five industries whose $\widehat{\beta_{1i}}$ are significantly positive based on Table 1 – Stones, Machinery, Electronics Equipment, Autos and Others, and Aerospace – and equals zero otherwise. Φ is the standard normal distribution function. We estimate the LPM and the probit model employing each of the persistence measures, with and without the outlier industries.

Table 3 summarizes the estimation results of (12). Columns 2 and 3 report those of the LPM; Columns 4 and 5 present those of the probit model. All eight estimated coefficients on the persistence are positive, one is significant at the 10% level, one significant at the 5% level, and five are significant at the 1% level. For example, according to the LPM estimates for the full sample, industries with 10% higher AR(1) persistence measure are associated with 12.79% higher probability for their R&D to be pro-cyclical. The corresponding statistic with the Cochrane persistence measure is 30.67%. Although these preliminary results are based on a very small cross-section sample, they are consistent with our theoretical prediction higher persistence causes R&D more likely to appear pro-cyclical.

3.5 Panel evidence

To test our theory with more observations and higher degrees of freedom, we run the following panel regression:

$$\triangle \ln R_{it} = \beta_i + \beta_1 \triangle \ln Y_{it} + \beta_2 \rho_i \triangle \ln Y_{it} + \gamma X_t + \epsilon_{it}. \quad (13)$$

Compared to (9), (13) replaces the constant with industry dummy β_i, and adds an interaction term $\rho_i \triangle \ln Y_{it}$. X_t is a vector of exogenous controls as in (9) including a quadratic time trends allowed to differ before and after 1980 and a post-1992 dummy. Under this specification, the estimate on β_1 captures the average cyclicality of industry R&D, while that on β_2 reflects an additional impact of persistence. $\beta_2 > 0$ under the null: higher ρ_i makes R&D more likely to be pro-cyclical.

Alternatively, (13) can be interpreted as follows: ρ_i reflects the extent to which present production will be carried into the future, so that $\rho_i \triangle \ln Y_{it}$ captures the expected future production. In other words, (15) estimates the correlation between present R&D and present production, controlling for the expected future production. Our results are robust to replacing the industry fixed effect by the persistence measure ρ_i or including lagged output. In this paper we report estimates on the contemporaneous relationship between R&D growth and output growth only. The estimated cumulative correlation in one year and two years stay qualitatively similar, and are available upon request.

Table 4 summarizes the estimation results of (13). Panel 1 reports the results *without* controlling for $\rho_i \triangle \ln Y_{it}$ for comparison. Panel 2 reports those with ρ_i as the Cochrane measure; Panel 3 presents those with the AR(1) measure.

3.5.1 OLS estimation

Column 2 of Table 4 presents the OLS results of (13). In Panel 1 of Column 2, without controlling for $\rho_i \triangle \ln Y_{it}$, industry R&D is pro-cyclical on average: 10% higher output growth is associated with 1.01% higher R&D growth, significant at the 5% level. In Panel 2 of Column 2, once $\rho_i \triangle \ln Y_{it}$ is included with ρ_i as the Cochrane measure, the estimated coefficient on $\triangle \ln Y_{it}$ becomes significantly negative. In Panel 3 of Column 2, with ρ_i as the AR(1) measure, the estimated coefficient on $\triangle \ln Y_{it}$ remains positive, but becomes small quantitatively small and statistically insignificant. Most importantly, the OLS estimated coefficients on $\rho_i \triangle \ln Y_{it}$ are positive and statistically significant at the 1% level in both Panel 2 and Panel

3 of Column 2. This is consistent with our theory, implying R&D co-moves with output more strongly for industries with higher persistence.

3.5.2 IV Estimation

Interestingly, Column 2 of Table 4 shows the OLS point estimate of the coefficient on $\rho_i \triangle \ln Y_{it}$ with ρ_i as the Cochrane measure is almost twice as big as that with the AR(1) measure. This implies the Cochrane measure displays a stronger correlation with the magnitude of the pro-cyclicality of industry R&D. However, the estimate with the Cochrane measure may be upper biased: according to Fatas (2000),the causality can run from R&D to persistence. Such upper bias, although presumably smaller, can also be present for the estimates with the AR(1) measure, as controlling for mean R&D level may not capture all the impact of innovation on persistence.

To correct for such potential bias, we implement an instrumental-variable (IV) approach with demand-shift instruments, treating both $\triangle \ln Y_{it}$ and $\rho_i \triangle \ln Y_{it}$ as endogenous. The assumption is that demand influences production directly, and affects R&D only indirectly through its impact on $\triangle \ln Y_{it}$ and $\rho_i \triangle \ln Y_{it}$. Demand's influence on persistence can arise from the persistence in demand itself or, alternatively, from persistence in output's response to demand fluctuations due to, for example, production adjustment cost that can vary by industry.

While finding good instruments that are both perfectly exogenous to industry R&D and substantially relevant to industry output is difficult in practice, we implement three aggregate instruments that have frequently been applied in the literature. The first two follow Ramey (1991), Shea (1993), and Ouyang (2010), using aggregate output as demand-shift instruments for disaggregate industries. In particular, we apply the growths in real GDP and in Industrial Production (IP) Index. The third instrument is taken from Basu, Fernald, and Kimball (hereafter BFK) (2006) as a vector of monetary shocks, government spending, and oil-price shocks.[7]

The two-stage least-square estimations treat $\triangle \ln Y_{it}$ and $\rho_i \triangle \ln Y_{it}$ as endogenous and employ current value, one lag, and one lead of each instrumental variable. We employ the instrument lag because aggregate shocks can have a lagged effect on industry output. We apply instrument lead because unobservable shocks to final demand may be first reflected as intermediate output before they are reflected in measured final output, and because future shocks can influence present output if they are fully or partially anticipated. Hence, the IV estimates of the coefficients on $\triangle \ln Y_{it}$ and $\rho_i \triangle \ln Y_{it}$ reflect both the response of R&D to output changes attributable to aggregate shocks, and how cyclical persistence affects the properties of such response.

Columns 3, 4 and 5 of Table 4 summarize the IV estimation results employing, correspondingly, the real GDP growth, the IP growth, and the BFK shocks. Panel 1 shows, without controlling for $\rho_i \triangle \ln Y_{it}$, all three IV estimates on the output coefficient are positive, two significant at the 10% level. This is consistent with Ouyang (2010) suggesting R&D responds positively to demand-driven output fluctuations. However, once $\rho_i \triangle \ln Y_{it}$ is included as an additional endogenous term, all six IV estimates on the output coefficient turn negative; four are significant at the 10% level or above. Most importantly, all six IV estimates on the coefficient of $\rho_i \triangle \ln Y_{it}$ are positive and statistically significant, and much bigger in point estimates compared to the corresponding OLS estimates. Hence, the IV estimation not only generates results consistent with the OLS results, but outperforms the OLS results.

While the IV estimation results again support the theory, aggregate output and the BFK shocks cannot be ideal instruments. A good instrument is supposed to be relevant to industry output but exogenous to industry R&D. All three instruments are relevant, suggested

[7] The monetary shocks are measured as the quarterly VAR innovations to the 3-month Treasury bill rate, government spending as the quarterly growth of real government spending, and the oil-price shocks as the difference between the log of the real refiner acquisition price for crude oil and its maximum value in the preceding four quarters. Following Basu et al. (2006), we take the sum of the quarterly shocks in the preceding calendar year as our annual instruments. See Basu et al. (2006), Appendix I, for details.

by the Anderson-Rubin F statistic for the first-stage joint significance of the output terms. However, they may not be exogenous. Aggregate output may reflect common technology shocks that impact industry R&D directly. Monetary shocks can influence industries' ability to finance R&D. Government spending can affect industrial R&D through a spill-over effect from publicly-financed R&D. Oil-price shocks may change the relative R&D cost. Unfortunately, identifying instruments that are completely un-correlated with R&D while, at the same time, sufficiently correlated with output is a difficult, if not impossible. Table 4 reports the Hansen J statistics as an over-identification test: according to the P values, we cannot reject the null that the instruments are *not* correlated with the second-stage regression residual for any of the IV regressions, implying a reasonable exogeneity of the instruments.

In summary, Table 4 suggests the following. While both OLS and IV regression results show industry R&D is pro-cyclical on average, controlling for cyclical persistence turns all the output coefficients either statistically insignificant or significantly negative. The OLS results suggest R&D is more procyclical for industries with higher persistence; the IV results imply R&D responds more positively and strongly to output fluctuations driven by aggregate shocks for industries with higher persistence. Moreover, the IV estimates outperforms the OLS estimates based on the point estimates. This is again consistent with the null, implying cyclical persistence as a useful factor influencing industry R&D's cyclicality.

3.6 Persistence and Liquidity Constraint

Liquidity constraint has been proposed as another notable explanation for pro-cyclical R&D by Aghion et al. (2005) and Ouyang (2010). They argue binding liquidity constraint hinders the optimal timing of innovation, causing R&D to lower during recessions. Cyclical persistence and liquidity constraint do not contradict each other: the former *impacts* the optimal timing, while the latter *hinders* the optimal timing. As a matter of fact, cyclical persistence and liquidity constraint can drive R&D pro-cyclical by working together.

To examine whether the impact of liquidity constraint and cyclical persistence are both present on R&D's cyclicality, we adopt a methodology by Ouyang (2010). Ouyang (2010) argues binding liquidity constraint prevents R&D from rising but not from declining. Therefore, if the optimal timing of R&D is counter-cyclical, then the cyclical response of R&D should be asymmetric: it moves in the same direction with output when output declines due to binding constraint, and in the opposite direction when output rises due to lower opportunity cost.[8] But according to our theory: the optimal timing of R&D may not be counter-cyclical, especially when cyclical persistence is sufficiently high.

To investigate whether the impact of liquidity constraint and persistence are both present in our panel, we test the following:

$$\triangle \ln R_{it} = \beta_i + \beta_1^h D^h \triangle \ln Y_{it} + \beta_2^h D^h \rho_i \triangle \ln Y_{it} + \beta_1^l D^l \triangle \ln Y_{it} + \beta_2^l D^l \rho_i \triangle \ln Y_{it} + \gamma X_t + \epsilon_{it}. \quad (14)$$

Compared to (13), (14) allows β_1 and β_2 to differ for increases and decreases in output. $D^h = 1$ when $\triangle \ln Y_{it} \geq \triangle \ln Y_{it-1}$ and equals zero otherwise; $D^l = 1$ when $\triangle \ln Y_{it} < \triangle \ln Y_{it-1}$ and equals zero otherwise. β_i is the industry dummy; X_t is a set of exogenous controls as in (9) and (13).

Under the null of persistence *and* liquidity constraint, persistence influences R&D's response only when liquidity constraint does not bind: $\beta_2^h > 0$ and $\beta_2^l = 0$. In other words, when output decreases, R&D declines with output due to binding liquidity constraint; when output rises, R&D may increase or decrease, depending on persistence. The underlying assumption is that liquidity constraint binds only when output declines. If liquidity constraint binds always, then R&D would co-move with output always; in that case, $\beta_2^h = \beta_2^l = 0$. Conversely, $\beta_2^h > 0$ and $\beta_2^l > 0$ if liquidity constraint never binds.

We perform both OLS and IV estimations of (16) employing real GDP growth, IP growth, and BFK shocks as instruments. The results are summarized in Table 5. Panel 1 reports those without $\rho_i \triangle \ln Y_{it}$: the OLS estimate on output increases is positive, but statistically

[8] Ouyang (2010) argues this does not imply that R&D never rises, as it captures R&D's response to demand shocks only while, in practice, there can be supply shocks that drive R&D and output to rise together.

insignificant; the OLS estimate on output decreases is positive and statistically significant at the 10% level. All three IV estimates on output increases are negative and significant at the 10% level or above; all three IV estimates on output decreases are positive and significant at the 10% level or above. These results suggest pro-cyclical industry R&D comes from that R&D tracks output declines (OLS results) and R&D's response to output fluctuations driven by aggregate shocks are asymmetric (IV results), consistent with Ouyang (2010).

The OLS and IV estimation results of (16) with $D^h \rho_i \triangle \ln Y_{it}$ and $D^l \rho_i \triangle \ln Y_{it}$ are reported in Panels 2 and 3 of Table 5. The first two rows of each panel present the estimates on β_1^h and β_2^h, the coefficients corresponding to output increases. All estimates on β_1^h remain negative and six remain statistically significant. More importantly, all eight estimates on β_2^h, the coefficient of $D^h \rho_i \triangle \ln Y_{it}$, are positive, and six are significant at the 10% level or above. Also, the point estimates on β_1^h is bigger in absolute values compare to the corresponding estimates in Panel 1when the estimates on β_2^h are statistically significant. This implies, for industries with higher persistence, R&D tends to decrease *by less* or even increase when output rises. In other words, the impact of persistence on R&D's response is present when output rises, consistent with the null.

The third and fourth rows of Panels 2 and 3 report the estimates on β_1^h and β_2^h, the coefficients corresponding to output decreases. None of the estimates on β_2^l is statistically significant, suggesting the influence of persistence is *not* present when output declines. As a matter of fact, all 16 estimates on either β_1^l and β_2^l are statistically insignificant. This suggests the specification of including $D^l \rho_i \triangle \ln Y_{it}$ is not favorable to estimate how R&D responds to output decreases. While the results are not reported here, we experimented with dropping $D^l \rho_i \triangle \ln Y_{it}$ when estimating (16), and find the estimated β_1^l remain positive and statistically significant as in Panel 1 of Table 5. We interpret this as R&D's responses to output decreases is driven by binding constraint rather than persistence.

In summary, the results in Table 5 are consistent with the null: the impact of persistence and liquidity constraint on R&D's cyclicality are both present, liquidity constraint drives

R&D and output to decline together, while higher persistence raises R&D's response when output rises and when liquidity constraint does not bind.

4 Conclusion

We propose one additional factor influencing the optimal timing of innovation – cyclical persistence. By analyzing a simple two-period model, we posit the cyclicality of innovation is determined by the cyclical responses of two factors: innovation's marginal return and its marginal opportunity cost. Higher persistence raises the cyclical response of innovation marginal return, and drives R&D procyclical. We carry our theory to an industry panel of output and R&D. We find cyclical persistence, measured in various ways, helps to account for the observed cross-industry differences in R&D's cyclicality.

However, cyclical persistence cannot be the only influence on the cyclicality of innovation. In addition to innovation's opportunity cost originally proposed by Schumpeter (1939) and liquidity constraint argued by Aghion et al. (2005), several other influences have been proposed by the recent literature. These include Fatas (2000) who models pro-cyclical labor supply, Barlevy (2007) who stresses dynamic externalities inherent to the innovation process, and Francois and Lloyd-Ellis (2009) who separates innovation into three stages in which R&D rises during the implementation boom. All these factors are likely imporant for R&D's cyclicality in reality. As a matter of fact, our estimation results suggest the influence of persistence and liquidity constraint on R&D's cyclicality are both present in our panel. Future research should evaluate the quantitative influence of each of these factors on the cyclicality of R&D, to shed light on how short-run cycles and long-run growth are linked together through the innovation channel.

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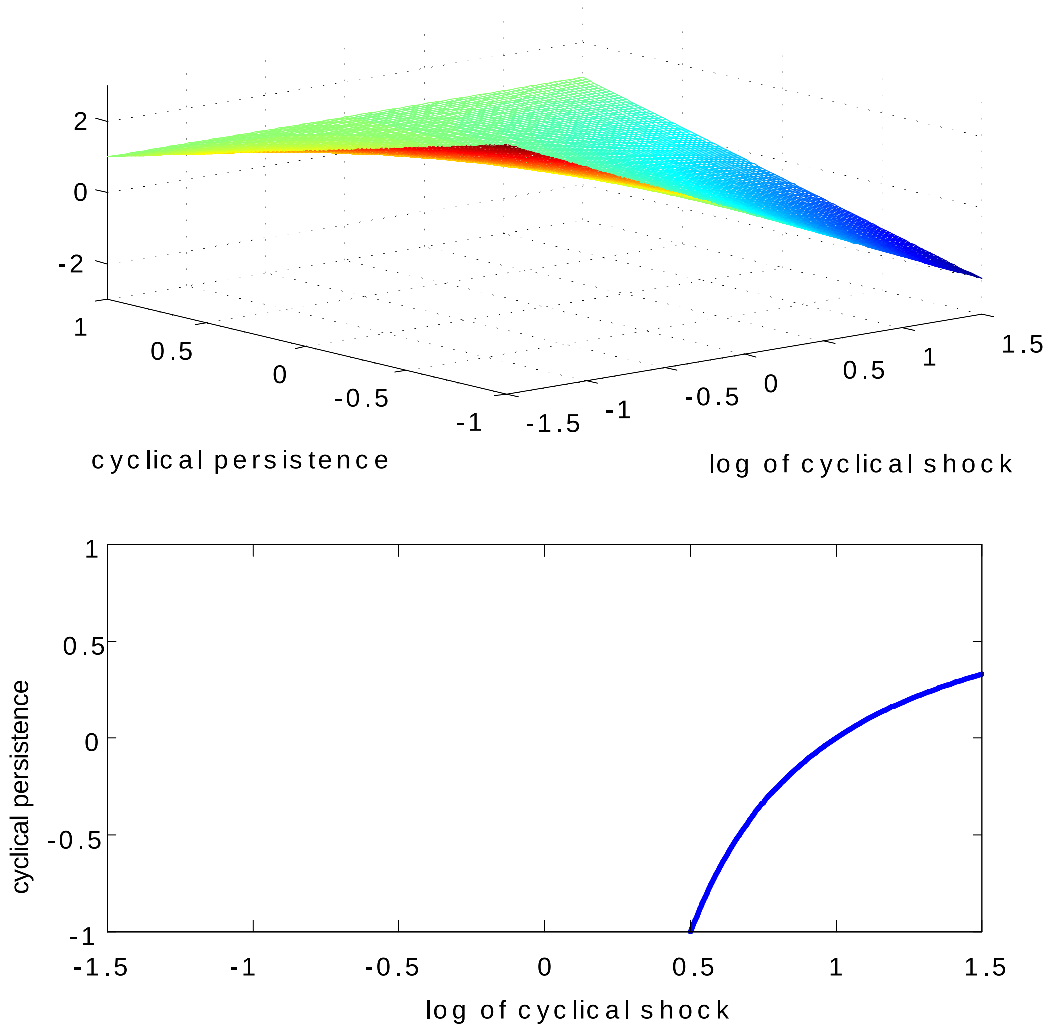

Figure 1: Cyclical shock (ε), cyclical persistence (ρ), and the value of $1-(1-\rho)\ln(\varepsilon)$ for Proposition 2 to hold. Higher ρ makes innovation less likely to appear counter-cyclical when $1-(1-\rho)\ln(\varepsilon)>0$. The top panel plots the value of $1-(1-\rho)\ln(\varepsilon)$ against $\rho\in[-1,1]$ and $\ln(\varepsilon)\in[-1.5,1.5]$; blue colorred surface indicates where $1-(1-\rho)\ln(\varepsilon)$ falls below zero. The blue curve in the bottom panel indicate the value combinations of ρ and $\ln(\varepsilon)$ where $1-(1-\rho)\ln(\varepsilon)$ hits zero. Any value combinations of ρ and $\ln(\varepsilon)$ inside the blue curve generate $1+\rho\ln(\varepsilon)$ below zero.

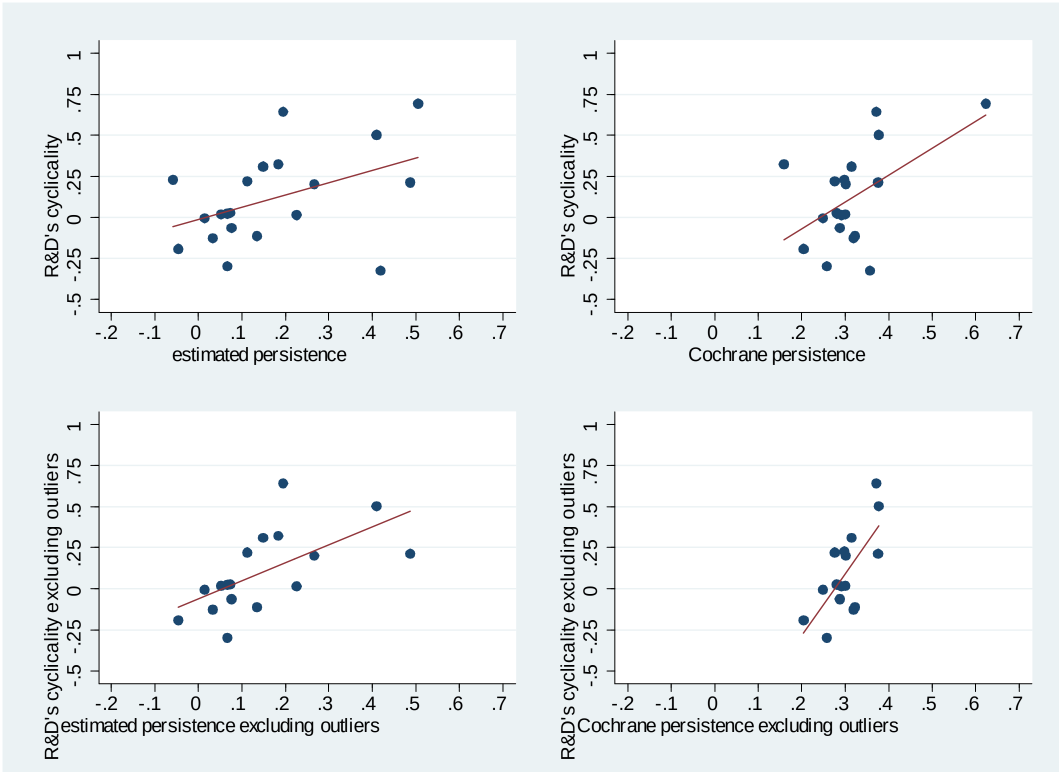

Figure 2: R&D's cyclicality and cyclical persistence. Each dot represents an industry; the lines are the fitted linear relationship. R&D's cyclicality is measured as $\widehat{\beta_{i1}}$ summarized in Table 1 that captures the comovement between R&D growth and output growth. The estimated persistence is the estimated AR(1) coefficient based on (11); the Cochrane persistence is constructed based on (10); both measures are summarized in Table 1. The top two panels presents the plots for the full sample; the bottom two panels present those excluding outlier industries as those with the highest or the lowest persistence as well as those with the highest or the lowest estimate on $\widehat{\beta_{i1}}$. See notes to Tables 1 for data sources. See text for details.

b

Industry	**1987 SIC**	**Corr**(R_t, Y_t)	$\widehat{\beta_{i1}}$	Cochrane	AR(1)
Food	20, 21	0.0741	0.0269	0.2044	0.0731
Textile	22,23	0.1514	0.3098	0.2795	0.1486
Lumber	24,25	0.0193	−0.1131	0.3007	0.1346
Paper	26	−0.0787	−0.1931	0.3225	−0.0457
Industry Chemicals	281,282, 286	−0.1069	−0.0633	0.3140	0.0761
Drugs	284	0.2243	0.3229	0.2871	0.1833
Other Chemicals	283, 285, 287, 289	−0.1501	−0.2984	0.1589	0.0667
Petroleum	29	−0.3144	−0.1263**	0.2579	0.0330
Rubber	30	0.1866	0.2203	0.3188	0.1123
Stones	32	0.3208	0.6424**	0.2758	0.1947
Furrous Metals	331, 332, 339	0.0327	0.0188	0.3711	0.0517
Non-Ferrous Metals	333, 334, 335, 336	−0.0690	−0.0049	0.2996	0.0142
Metal Products	34	0.1050	0.0142	0.2488	0.2256
Machinery	35	0.1627	0.5022**	0.2910	0.4096**
Eletronics Equip.	366-367	0.4594	0.2122**	0.3767	0.4866**
Other Equip.	361-365, 369	0.0672	0.0228	0.3753	0.0670
Autos and Others	371, 373-75, 379	0.4363	0.2274**	0.2813	−0.0586
Aerospace	372, 376	0.3736	0.6917***	0.2976	0.5053***
Scientific Instruments	381,382	−0.0537	−0.3243	0.6236	0.4185**
Other Instruments	384-387	0.3484	0.2010	0.3570	0.2664*
average		0.1047	0.1351*	0.3121	0.1858**

Table 1: The Cyclicality of R&D and The Cyclical Persistence of 20 Manufacturing Industries. corr(R, Y) is the time-series correlation between R&D growth and output growth; $\beta 1$ is the OLS estimate on output coefficient of equation (9) in the text, regressing R&D growth on a constant and output growth; Data on output is from the NBER Manufacturing Productivity database; data on R&D by industry is from the NSF. Based on robust standard errors, * indicates significance at the 10% level; ** indicates significance at the 5% level; *** indicates significance at the 1% level. See text for details.

$$\widehat{\beta_{i1}} = \nu + \lambda\rho_i + \tau_i$$

	AR(1) Measure		Cochrane Measure	
indep. var.	**Full sample**	**No outliers**	**Full sample**	**No outliers**
Persistence	0.7434^{*} (0.4244)	1.1003^{***} (0.3511)	1.6287^{**} (0.5782)	3.8002^{***} (0.9799)
Constant	-0.0105 (0.0670)	-0.0620 (0.0571)	-0.3938^{*} (0.1952)	-1.0464^{***} (0.2807)
# of obs.	20	17	20	17
R^2	0.1965	0.3784	0.2729	0.4949

Table 2: Industry R&D's cyclicality and cyclical persistence. The OLS results by regressing the estimated R&D's cyclicality, namely, the estimated output coefficients in (9), on a constant and persistence measure for the full sample and for the restricted sample excluding the outlier industries. The outlier industries are those either with the highest or the lowest measure on persistence or with the highest or the lowest estimates on R&D's cyclicality. The outlier industries excluded under the AR(1) measure are Aerospace, Scientific Instruments, and Autos and Others; those excluded under the Cochrane measure are Aerospace, Scientific Instruments, and Drugs. Robust standard errors are in parentheses. See text for details.

	LPM		Probit	
indep. var.	Full Sample 20 obs.	No Outliers 18 obs.	Full Sample 20 obs.	No Outliers 18 obs.
AR(1) Measure	1.2778^{*}	1.5936^{**}	3.7685	7.1728^{***}
	(0.6527)	(0.6098)	(2.3344)	(2.6720)
constant	0.0350	$-.0916$	-1.3953^{**}	-2.5893^{***}
	(0.1442)	(0.0688)	(0.6522)	(0.7981)
Log-likelihood	-	-	-9.1051	-4.7217
Pseudo R-squared	0.2374	0.3856	0.1904	0.4178
Cochrane Measure	3.0667^{***}	5.7872^{***}	29.4962^{***}	29.4962^{***}
	(0.6526)	(1.9150)	(11.2570)	(11.2901)
constant	-0.7070^{***}	-1.5329^{**}	-10.1907^{***}	-10.1907^{***}
	(0.6526)	(0.5581)	(3.8406)	(3.8519)
Log-likelihood	-	-	-5.3008	-5.3008
Pseudo R-squared	0.3958	0.3861	0.5287	0.4440

Table 3: LPM and Probit Estimations of the impact of cyclical persistence on industry R&D's being pro-cyclical for the full sample and for the sample excluding outlier industries LPM refers to the Linear Probability Model. The LPM is estimated as ordinary least square and the probit model is estimated using maximum likelihood. The dependent variable is a dummy that equals one if the estimate on output growth in (9), as listed in the fourth column of Table 1, is positive and significant at 10% level or above. The Pseudo R-squared for the LPM is just the usual R-squared for OLS; the Pseudo R-squared for probit is calcuated according to Wooldrige (2002). Robust standard errors are in parentheses. * indicates significance at 10% level. ** indicates significance at 5% level. *** indicates significance at 1% level. See text for details. See notes to Table 2 for outlier industries. See notes to Tables 1 for data sources.

indep. var.	OLS	IV(i)	IV(ii)	IV(iii)
Panel 1: $\triangle \ln \mathbf{R}_{it} = \beta_i + \beta_1 \triangle \ln \mathbf{Y}_{it} + \gamma \mathbf{X}_t + \epsilon_{it}.$				
$\triangle \ln Y_{it}$	0.1016^{**} (0.0672)	0.1585^{*} (0.0817)	0.1356^{*} (0.0677)	0.0424 (0.0750)
Anderson-Rubin F-Stat	4.95	2.43	2.77	3.33
P-value	0.0263	0.0639	0.0409	0.0031
Hansen-J Stat.	-	4.787	7.507	7.059
P-value		0.3098	0.1114	0.4228
$\triangle \ln \mathbf{R}_{it} = \beta_i + \beta_1 \triangle \ln \mathbf{Y}_{it} + \beta_2 \rho_i \triangle \ln \mathbf{Y}_{it} + \gamma \mathbf{X}_t + \epsilon_{it}.$				
Panel 2: ρ_i as Cochrane measure				
$\triangle \ln Y_{it}$	-0.3527^{**} (0.1410)	-1.7298^{*} (1.0242)	-1.9916^{**} (0.9769)	-2.8164^{***} (1.0824)
$\rho_i \triangle \ln Y_{it}$	1.4823^{***} (0.4117)	6.0483^{*} (3.2784)	6.8955^{**} (3.1642)	9.2050^{***} (3.5061)
Anderson-Rubin F-Stat	4.17	2.43	2.77	2.72
P-value	0.0158	0.0639	0.0409	0.0040
Hansen-J Stat.	-	0.192	0.257	10.300
P-value		0.6608	0.6125	0.1722
Panel 3: ρ_i **as AR(1) measure**				
$\triangle \ln Y_{it}$	0.0032 (0.0785)	-0.2361 (0.2365)	-0.2806 (0.2275)	-0.5141^{**} (0.2076)
$\rho_i \triangle \ln Y_{it}$	0.7680^{***} (0.2177)	2.9008^{*} (1.6232)	3.0280^{**} (1.5328)	3.8710^{***} (1.4269)
Anderson-Rubin F-Stat	7.40	2.43	2.77	2.72
P-value	0.0007	0.0639	0.0409	0.0040
Hansen-J Stat.	-	0.002	0.788	10.779
P-value		0.9607	0.3748	0.1486

Table 4: Panel estimation results of the cyclicality of R&D and cyclical persistence. The sample size is 800. The two-stage least-square estimation threats the output terms as endogenous and employs the current value, one lag, and one lead of each instrumental variable. The results summarized under IV(1) are from estimation with the real GDP growth as the instrument; those under IV(2) are from estimation with the IP growth as the instrument; and those under IV(3) are from estimation with the monetary shocks, government spending, and oil-price shocks by Basu et al. (2006). The Anderson-Rubin F-stat. for weak instruments and the Hansen-J stat. for over identification are computed based on Baum et al. (2007). The Anderson-Rubin F-stat. for OLS is the F statistics that test the joint significance of the output terms. Robust standard errors clustered by industry are in parentheses. * indicates significance at the 10% level. ** indicates significance at the 5% level. *** indicates significance at the 1% level. See notes to Table 1 for data sources and cyclical persistence measures. See text for more details.

indep. var.	OLS	IV(i)	IV(ii)	IV(iii)
Panel 1: $\triangle \ln R_{it} = \beta_i + \beta_1 D^h \triangle \ln Y_{it} + \beta_2 D^l \triangle \ln Y_{it} + \gamma X_t + \epsilon_{it}$.				
$D^h \triangle \ln Y_{it}$	0.1246 (0.1035)	-0.8710^{*} (0.4334)	-0.6449^{**} (0.3243)	-0.9425^{*} (0.5527)
$D^l \triangle \ln Y_{it}$	0.1440^{*} (0.0652)	0.6777^{***} (0.2415)	0.5517^{***} (0.2012)	0.5305^{*} (0.2876)
Anderson-Rubin F-Stat P-value	-	5.08 0.0094	7.02 0.0020	2.50 0.0584
Hansen-J Stat. P-value	-	0.301 0.5832	1.129 0.2879	0.983 0.3215
$\triangle \ln \mathbf{R}_{it} = \beta_i + \beta_1^h \mathbf{D}^h \triangle \ln \mathbf{Y}_{it} + \beta_2^h \mathbf{D}^h \rho_i \triangle \ln \mathbf{Y}_{it} + \beta_3^l \mathbf{D}^l \triangle \ln \mathbf{Y}_{it} + \beta_4^l \mathbf{D}^l \rho_i \triangle \ln \mathbf{Y}_{it} + \gamma \mathbf{X}_t + \epsilon_{it}$.				
Panel 2: ρ_i **as Cochrane measure**				
$D^h \triangle \ln Y_{it}$	-0.5250 (0.3260)	-3.6135^{*} (1.9565)	-3.185^{**} (1.5025)	-4.0852^{**} (1.9350)
$D^h \rho_i \triangle \ln Y_{it}$	1.8804^{*} (0.9914)	11.8544^{*} (7.1870)	10.0848^{*} (5.6645)	11.9606^{*} (6.7061)
$D^l \triangle \ln Y_{it}$	-0.3103 (0.2951)	1.4956 (2.5533)	0.6525 (2.1181)	-1.7375 (2.6448)
$D^l \rho_i \triangle \ln Y_{it}$	1.2767 (0.9662)	-4.4624 (8.7896)	-1.6054 (7.1980)	6.4107 (9.0564)
Anderson-Rubin F-Stat P-value	-	2.65 0.0104	2.65 0.0104	2.72 0.0040
Hansen-J Stat. P-value	-	3.527 0.3173	4.651 0.1992	4.577 0.4697
Panel 3: ρ_i **as AR(1) measure**				
$D^h \triangle \ln Y_{it}$	-0.1389 (0.1067)	-0.8226^{**} (0.4181)	-0.6153^{*} (0.3436)	-1.0953^{**} (0.4894)
$D^h \rho_i \triangle \ln Y_{it}$	1.2493^{***} (0.3208)	4.5549 (3.1853)	2.5553 (2.1359)	4.8464^{*} (2.7753)
$D^l \triangle \ln Y_{it}$	0.0912 (0.0791)	0.0777 (0.3634)	-0.14278 (0.3505)	-0.2006 (0.3381)
$D^l \rho_i \triangle \ln Y_{it}$	0.1761 0.4898	1.3742 (2.7565)	2.9967 (2.4076)	3.8306 (2.4505)
Anderson-Rubin F-Stat P-value	-	2.97 0.0072	2.65 0.0104	2.72 0.0040
Hansen-J Stat. P-value	-	3.753 0.1531	5.519 0.1375	4.364 0.4983

Table 5: Persistence and Liquidity Constraint. This table reports the estimation results by allowing the coefficients of the output terms to differ for output increases and output decreases. The null is persistence has impact only when output rises. Robust standard errors clustered by industry are in parentheses. * indicates significance at the 10% level. ** indicates significance at the 5% level. *** indicates significance at the 1% level. See notes to Table 1 for data sources and cyclical persistence measures. See notes to Table 4 for results assuming common coefficients on output increases and decreases. See text for more details.

5 Appendix:

5.1 Discrete Production Shocks: Robustness Check

In our model, ε takes continuous value, but it can take discrete values in a different set up. For example, suppose that ε follows a two-state Markov process with values ε^l and ε^h; ε persists with probability ρ and switches value with probability $1-\rho$: $E\left(\varepsilon_{t+1}|\varepsilon_t=\varepsilon^i\right)=\varepsilon^{-i}+\rho\left(\varepsilon^i-\varepsilon^{-i}\right)$, where $i=h,l$. Suppose that the standard assumptions hold and an interior solution exists. The first-order condition with respect to R gives:

$$\varepsilon^i\alpha(1-R^*)^{\alpha-1}=\frac{\phi\left(\gamma-1\right)}{1+r}\left[\varepsilon^{-i}+\rho\left(\varepsilon^i-\varepsilon^{-i}\right)\right]-\phi c,\ \ i=h,l. \tag{3}$$

Let R_h to be the optimal R^* with ε^h, and R_l to that with ε^l. It can be shown that $R_h<R_l$ if and only if $\frac{(\gamma-1)(1-\rho)}{(1+r)}\left(\varepsilon^h+\varepsilon^l\right)>c$.

To see whether Propositions 1 and 2 apply to this case, assume that ε rises from ε^l to ε^h. Then the change in the marginal expected return to innovation is $\frac{\phi(\gamma-1)}{1+r}\left(2\rho-1\right)\left(\varepsilon^h-\varepsilon^l\right)$; and the change in the marginal opportunity cost of innovation *before the entrepreneur chooses a new* R^*, is $\left(\varepsilon^h-\varepsilon^l\right)\alpha(1-R_l)^{\alpha-1}$, which equals $\left(\varepsilon^h-\varepsilon^l\right)\left\{\frac{\phi(\gamma-1)}{1+r}\left[\rho+\left(1-\rho\right)\frac{\varepsilon^h}{\varepsilon^l}\right]-\frac{\phi c}{\varepsilon^l}\right\}$. With $\frac{(\gamma-1)(1-\rho)}{(1+r)}\left(\varepsilon^h+\varepsilon^l\right)>c$, the latter dominates the former and R^* must decline for (10) to hold. This is consistent with Proposition 1.

In this case, x, the magnitude of the change in the marginal opportunity cost relative to that in the marginal expected return, is:

$$x=\left(\varepsilon^h-\varepsilon^l\right)\left[\frac{\phi\left(\gamma-1\right)}{1+r}\left(1-\rho\right)\left(1+\frac{\varepsilon^h}{\varepsilon^l}\right)-\frac{\phi c}{\varepsilon^l}\right] \tag{4}$$

Apparently, $\frac{dx}{d\rho}<0$. Higher ρ reduces this relative magnitude, so that innovation is less likely to decline in response to an increase in ε from ε^l to ε^h. This is, again, consistent with Proposition 2.