Virtue of Bad Times and Financial Market Frictions

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Aug 2010

Abstract

Schumpeter (1939) proposes that recessions have virtue in promoting growth-enhancing activities. However, this view is often at odds with data, as many innovative activities appear pro-cyclical. We revisit the "virtue of bad times" theoretically and empirically. Our theory suggests that recessions have such virtue only when the cyclicality of innovation's marginal opportunity cost dominates that of its marginal expected return; but binding financial constraints can hinder such virtue, preventing innovation from rising during recessions. Our theory is carried to an industry panel of production and innovation. Our evidence suggests that recessions indeed have potential virtue, but such virtue is hindered by financial-market frictions.

JEL codes: E32, E44, O30.

Key words: recessions, growth, R&D, financial-market frictions.

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1 Introduction

Bad times are said to have virtue in promoting long-run growth. This idea traces back to Schumpeter (1939), and has been revived theoretically in the past 20 years by many researchers such as Hall (1991), Aghion and Saint-Paul (1998), and Davis et al. (1999). They argue that activities such as R&D, reallocation, or reorganization are concentrated during recessions when their opportunity cost as forgone output is low. Therefore, bad times promote long-run growth by encouraging growth-enhancing activities. Unfortunately, data often fail to support this view. For example, contrary to its prediction, R&D appears pro-cyclical both at the aggregate level and at the industry level (Fatas, 2000; Ouyang, 2009). This has motivated some researchers to question whether bad times indeed have virtue, and some others to argue that such virtue is hindered by financial-market frictions (Barlevy, 2007; Aghion et al. 2005).

This paper revisits the virtue of bad times theoretically and empirically. Our theory captures the Schumpeterian idea with a simple over-lapping generation model, in which innovation and production compete for resource as in the conventional theory. The model suggests that the conclusion of the conventional theory relies heavily on the magnitude of the cyclicality of innovation's marginal opportunity cost relative to that of its marginal expected future return. In other words, bad times have virtue if and only if the cyclical response of innovation's marginal opportunity cost dominates. Then we incorporate financial-market frictions into the theory following Aghion et al. (2005), modeling an additional cost required to adopt innovation outcome into production that is subject to financial constraint. Recessions cause or tighten binding constraints, so that innovation declines regardless of the cyclical responses of its marginal opportunity cost. Therefore, even if bad times have potential virtue, such virtue can be hindered by financial-market frictions.

Our theory makes testable predictions on whether bad times have potential virtue and whether such virtue is hindered by financial-market frictions. Entrepreneurs' financial strength is captured by μ, the ratio of financial resource over output, similar in spirit to the stan-

dard indicator in the finance and growth literature as aggregate credit over GDP (Levin et al., 2000, King and Levine, 1993). Our theory predicts μ to affect the level and the cyclicality of innovation. With binding financial constraints, the level of innovation should rise in μ cross-section. With the potential virtue of bad times hindered by financial-market frictions, innovation should appear counter-cyclical with sufficiently high μ, but pro-cyclical with sufficiently low μ, and display mixed cyclicality for μ whose value lies in the middle.

Our theory is carried to an industry panel. Data availability limits our analysis to 16 U.S. manufacturing industries with data on production, R&D, and finance from 1958 to 1998. We examine the cyclicality of industry R&D, and investigate whether industry financial strength contributes to its differences cross-industry. We approximate μ using values of liquid assets, which mitigate an industry's need to borrow externally, and of net worth, which can be used as collateral for borrowing. Our empirical findings are as follows.

Cross-section, stronger industry financial strength is associated with higher R&D level as well as a smaller probability of having pro-cyclical R&D; most interestingly, Petroleum Refining, who displays superior financial strength with its net-worth ratio and liquid-asset ratio well surpassing the rest of the sample, is also the only industry with counter-cyclical R&D, which, according to the conventional theory, implies the virtue of bad times. Our panel regression confirms such findings, and further suggests that stronger financial strength makes R&D to appear pro-cyclical less often for industries whose R&D displays mixed cyclicality. These results are consistent with our theory, pointing to the existence of potential virtue of bad times hindered by financial-market frictions.

The rest of the paper is organized as follows. Section 2 presents the theory. Section 3 simulates a simple version of our theory numerically. Section 4 carries the theory to data. We conclude in Section 5.

2 The Model

The economy is populated by overlapping generations of entrepreneurs who live for two periods. There are L entrepreneurs in each generation. Each period, young generation produce and innovate; old generation 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 generation; and $E = 1$ for old generation.

2.1 Production and Innovation

Output produced by an young entrepreneur, denoted Y_y, is determined by an endogenous productivity A, and a production function f :

$$Y_y = A\varepsilon f(E), \quad f' > 0,\ f'' \leq 0. \tag{1}$$

ε is a cyclical shock that follows a Markov process with support $\left[\varepsilon^l, \varepsilon^h\right] \subseteq \mathbb{R}_+$, where $\varepsilon^l < 1$ and $\varepsilon^h > 1$. The unconditional mean of ε is normalized to one, and its conditional mean satisfies $E_t(\varepsilon_{t+1}) = \varepsilon_t^\rho$, where $0 < \rho < 1$ captures the persistence. The key assumption regarding ε is that it has direct impact on production only. In other words, ε affects innovation only indirectly by influencing innovation's opportunity cost.[1] Higher ε raises present output, the present marginal product of labor, as well as the expected future cyclical productivity.

Innovation process takes two steps to complete. By the end of period one, R generates potential growth $\phi(R)$ in the endogenous productivity: $\phi(R) \geq 1$, $\phi(0) = 1$, and $\phi' > 0$. To adopt such gain into production, however, it requires an additional adoption cost $Ac(R)$ at the beginning of period two: $c(0) = 0$, $c' \geq 0$, and $c'' \geq 0$. The adoption cost is normalized

[1] This is one of the key assumptions in the conventional theory on the virtue of bad times. Ouyang (2009) proposes that technology shocks may have direct impact on innovation. However, this paper examines the impact of production shocks only as a revisit of the conventional theory.

by A, as more advanced technology can be costlier to adopt.

Let Y_o to be the output of an old entrepreneur who inherited A and put R into innovation when he was young. When $\phi(R)$ is adopted,

$$Y_o = A\phi(R)\,\varepsilon f(1). \tag{2}$$

Let r to indicate the interest rate. Suppose that, for any $R \in (0,1]$ and $\varepsilon \in \left[\varepsilon^l, \varepsilon^h\right]$, $\left(\frac{\phi(R)-1}{1+r}\right)\varepsilon f(1) > c(R)$. Thus, an old entrepreneur adopts $\phi(R)$ whenever possible.

Under this setup, innovation raises future productivity, but requires the sacrifice of present production. Young entrepreneurs choose R to balance this trade-off. Financial-market frictions affect R through their impact on old entrepreneurs' ability to cover $c(R)$.

2.2 Complete Financial Market

We simplify the supply side of the financial market by assuming that there are infinite number of credit suppliers who lend at an exogenous interest rate r. Under complete financial market, an entrepreneur receives output $\varepsilon f(1-R)$ by the end of period one, borrows $c(R)$ at the beginning of period two to adopt $\phi(R)$; then he produces in period two, receives output and returns $(1+r)\,c(R)$ by the end of period two. Suppose that price equals one and there is no inflation. Let V to be the present discounted value of an entrepreneur's life-time profit. With A normalized as one, a forward-looking young entrepreneur optimizes as follows:

$$\underset{R}{Max} \quad V(R,\varepsilon) = \varepsilon f(1-R) - c(R) + \frac{\phi(R)}{1+r}\varepsilon^{\rho} f(1), \tag{3}$$

The following assumption ensures the concavity of V and the existence of an unique interior solution.

Assumption 1: V is second-order differentiable in R; $V_{RR}(R,\varepsilon) < 0$, $\forall R \in (0,1)$, $\forall \varepsilon \in \left[\varepsilon^l, \varepsilon^h\right]$; $V_R(0,\varepsilon) > 0$, $V_R(1,\varepsilon) < 0$, $\forall\ \varepsilon \in \left[\varepsilon^l, \varepsilon^h\right]$.

The first-order condition with respect to R, $V_R(R,\varepsilon)=0$, gives:

$$\varepsilon f'(1-R)=\left[\frac{f(1)}{1+r}\varepsilon^{\rho}\phi'(R)-c'(R)\right] \tag{4}$$

The left-hand side of (4) captures the marginal opportunity cost of innovation as the forgone present output. The right-hand side is the marginal expected (net) return to innovation. (4) suggests that the optimal R balances the trade-off between present and future production, equating the marginal opportunity cost to the marginal expected return.

Let R^{**} to represent the optimal R under complete financial market. Differentiating (4) with respect to R and ε reflects the response of R^{**} to ε:

$$\frac{dR^{**}}{d\varepsilon}=\frac{f'(1-R^{**})-\frac{f(1)}{1+r}\phi'(R^{**})\rho\varepsilon^{\rho-1}}{V_{RR}(R^{**})} \tag{5}$$

According to Assumption 1, $V_{RR}(R^{**})$ is negative. Thus, the sign of $\frac{dR^{**}}{d\varepsilon}$ is determined by the magnitude of $f'(1-R^{**})$, the impact of ε on the marginal opportunity cost, relative to that of $\frac{f(1)}{1+r}\phi'(R^{**})\rho\varepsilon^{\rho-1}$, the impact of ε on the marginal expected return. Intuitively, higher ε raises innovation's marginal opportunity cost as well as its marginal expected return, so that whether higher ε encourages or discourages innovation depends on which effect dominates.

Proposition 1 *Under complete financial market, a positive production shock reduces innovation if and only if the cyclicality of innovation's marginal opportunity cost dominates that of its marginal expected return; in this case, innovation co-moves negatively with output over time.*

Put differently, $\frac{dR^{**}}{d\varepsilon}<0$ if and only $f'(1-R^{**})>\frac{f(1)}{1+r}\phi'(R^{**})\rho\varepsilon^{\rho-1}$. Let Y to be the total output of young and old generation divided by the generation size L:

$$Y=Y_y+Y_o=\varepsilon\left[f(1-R)+f(1)\right]. \tag{6}$$

Correspondingly, $\frac{dY}{d\varepsilon}=f(1-R)+f(1)-\varepsilon f'(1-R)\frac{dR}{d\varepsilon}$. Apparently, $\frac{dY}{d\varepsilon}>0$ when $\frac{dR^{**}}{d\varepsilon}<0$:

higher ε lowers innovation but raises production, so that innovation and output co-move negatively over time.

Proposition 1 captures the case emphasized by the conventional theories on the virtue of bad times. For example, Aghion and Saint-Paul (1998) model the expected return to innovation reaped over the entire future, including periods with high profitability and those with low profitability, so that the cyclical response of innovation's marginal expected return fails to dominate that of innovation's marginal opportunity cost. Caballero and Hammour (1994) model the opportunity cost of productivity growth realized by exit but its return embodied through entry; the cyclical response of entry fails to dominate that of exit, because the former is dampened by an entry cost increasing in the size of entry. Conversely, theories that question the virtue of bad times emphasize the dominance of the cyclicality of innovation's marginal expected return. For example, Barlevy (2007) argues that 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.

2.3 Incomplete Financial Market

When the financial market is incomplete, an old entrepreneur has limited ability to cover $c(R)$. We assume a time-invariant parameter μ to capture such ability. μ is the fraction of an old entrepreneur's wealth that can be used to finance $c(R)$ either directly or indirectly. μ can be the fraction of wealth as liquid assets for internal finance, or the fraction of it as net worth used as collateral for external borrowing. Since an entrepreneur is born with zero initial wealth in period one, his initial wealth in period two equals the period-one output. Therefore, the total amount of financial resource equals μY_y, where Y_y reflects the impact of the output cycle on en entrepreneur's financial ability and μ captures factors other than the output cycle. In spirit, μ is similar to a standard financial indicator in the finance and growth literature as the ratio of total credit divided by GDP (King and Levine, 1993; and

Levine et al., 2000).

With constraint $c(R) \leq \mu Y_y$, an entrepreneur optimizes as follows:

$$\underset{R}{Max}\ \varepsilon f(1-R) - c(R) + \frac{\phi(R)}{1+r}\varepsilon^{\rho} f(1) + \lambda\left[\mu\varepsilon f(1-R) - c(R)\right], \tag{7}$$

λ is the shadow value of the financial constraint. $\lambda > 0$ when the constraint binds and $\lambda = 0$ otherwise. The first-order conditions yield

$$\begin{aligned} \varepsilon f'(1-R) + \lambda\left[\mu\varepsilon f'(1-R) + c'(R)\right] &= \frac{\varepsilon^{\rho} f(1)}{1+r}\phi'(R) - c'(R), \\ \lambda\left[\mu\varepsilon f(1-R) - c(R)\right] &= 0, \\ \lambda &\geq 0 \text{ and } \mu\varepsilon f(1-R) - c(R) \geq 0. \\ \lambda &> 0 \text{ when } \mu\varepsilon f(1-R) - c(R) = 0 \end{aligned} \tag{8}$$

Like (4), (8) equates the marginal opportunity cost of innovation to its marginal expected return. The right-hand side of (8) is identical to that of (4). The left-hand side of (8) includes an additional term $\lambda\left[\mu\varepsilon f'(1-R) + c'(R)\right]$. When the constraint does not bind ($\lambda = 0$), (8) is equivalent to (4). When the constraint binds ($\lambda > 0$), an increase in R brings not only higher marginal opportunity cost but also tighter constraint.

Proposition 2 *Under incomplete financial market, for any given ε the financial constraint is less likely to bind with higher μ.*

Proposition 2 is easy to prove. Let $R^{**}(\varepsilon)$ to be the optimal innovation under complete financial market that satisfies (4) with production shock ε; define $\Phi(\varepsilon, \mu) = \mu\varepsilon f(1 - R^{**}(\varepsilon)) - c(R^{**}(\varepsilon))$. Apparently $\Phi_{\mu} > 0$: Φ monotonically increases in μ, given ε. Put intuitively, lower μ tends to cause or further tighten the binding constraint.

Let R^* to be the optimal innovation that satisfy (8) with binding constraint ($\lambda > 0$). (8) suggests $V_R(R^*) > 0$ and

$$\mu\varepsilon f(1-R^*) = c(R^*); \tag{9}$$

Proposition 3 captures the cyclicality of R^*.

Proposition 3 *Under incomplete financial market with binding constraint, a positive production shock raises innovation; innovation and output co-move positively over time.*

Differentiating (9) with respect to ε and R^* gives

$$\frac{dR^*}{d\varepsilon} = \frac{\mu f\left(1-R^*\right)}{c'\left(R^*\right)+\mu\varepsilon f'\left(1-R^*\right)} \tag{10}$$

(10) suggests $\frac{dR^*}{d\varepsilon} > 0$: higher ε raises R^* by relaxing the binding constraint. Combining (10) with (6) gives

$$\frac{dY}{d\varepsilon} = \frac{f\left(1-R^*\right)c'\left(R^*\right)}{c'\left(R^*\right)+\mu\varepsilon f'\left(1-R^*\right)} + f(1) \tag{11}$$

(11) suggests $\frac{dY}{d\varepsilon} > 0$: higher ε raises output. Thus, R^* and Y commove positively in response to ε; innovation is pro-cyclical.

Proposition 4 *Given ε, innovation is weakly increasing in μ.*

The proof takes several steps. Since $\Phi_\mu > 0$, the financial constraint binds with sufficiently low μ and does not bind with sufficiently high μ for any given ε. First, suppose μ is sufficiently low, the financial constraint binds, and an entrepreneur chooses R^*. Conditional on binding constraint, differentiating (9) with respect to μ and R^* gives

$$\frac{dR^*}{d\mu} = \frac{\varepsilon f\left(1-R^*\right)}{c'\left(R^*\right)+\mu\varepsilon f'\left(1-R^*\right)} \tag{12}$$

Apparently, $\frac{dR^*}{d\mu} > 0$: R^* is strictly increasing in μ. Second, suppose that the constraint does not bind with μ sufficiently high, and an entrepreneur chooses R^{**}. With $V_{RR}\left(R\right) < 0$ according to Assumption 1, $V_R\left(R^{**}\right) = 0$ and $V_R\left(R^*\right) > 0$ suggest $R^* < R^{**}$. Third, once an entrepreneur reaches R^{**}, further increases in μ no longer affect R^{**}. In summary, innovation is weakly increasing in μ.

3 An Example

To illustrate quantitatively how financial-market frictions influence the cyclicality of innovation, this section solves a version of the model in Section 2 with linear production function: $\varepsilon f(E) = \varepsilon E$. The adoption cost is also linear in R, $c(R) = cR$, where c is a constant. The return to innovation is concave, $\phi(R) = 1 + R^{\alpha}$, with $\alpha \in (0,1)$. $E_t(\varepsilon_{t+1}) = \varepsilon_t^{\rho}$. We further assume that $c(1+r) < \left(\varepsilon^l\right)^{\rho}$, which ensures $\frac{\varepsilon^{\rho}}{1+r} R^{\alpha} > cR$ for any $\varepsilon \in \left[\varepsilon^l, \varepsilon^h\right]$ and $R \in [0,1]$, so that $\phi(R)$ is adopted whenever possible.

Under complete financial market, an entrepreneur optimizes as follows:

$$\underset{R}{Max} \quad V(R) = \varepsilon(1-R) - cR + \frac{\varepsilon^{\rho}}{1+r}(1+R^{\alpha})$$

Suppose that $\frac{\alpha}{1+r} < \left(\varepsilon^l\right)^{1-\rho}$, so that Assumption 1 is satisfied for any $\varepsilon \in \left[\varepsilon^l, \varepsilon^h\right]$: $V(R)$ is concave in R, $V(0) > 0$, and $V'(1) < 0$. The first-order condition with respect to R yields:

$$R^{**} = \left[\frac{\alpha\varepsilon^{\rho}}{(1+r)(\varepsilon+c)}\right]^{\frac{1}{1-\alpha}}. \tag{13}$$

(13) suggests that $\frac{dR^{**}}{d\varepsilon} < 0$ if and only if $\rho < \frac{\varepsilon}{\varepsilon+c}$. In this case, the marginal opportunity cost of innovation is linear in ε; and the expected marginal return to innovation is linear in ε^{ρ}. The elasticity of ε^{ρ} with respect to ε equals ρ. The elasticity of the marginal cost of innovation (as the sum of the marginal opportunity cost and the marginal adoption cost) with respect to ε equals $\frac{\varepsilon}{\varepsilon+c}$: $\frac{\partial \ln(\varepsilon+c)}{\partial \ln \varepsilon} = \frac{\varepsilon}{\varepsilon+c}$. With $\rho < \frac{\varepsilon}{\varepsilon+c}$, the marginal cost of innovation is more responsive to ε than the marginal expected return, and innovation is counter-cyclical under complete financial market. This is consistent with Proposition 1.

Under incomplete financial market, an entrepreneur optimizes as follows:

$$\underset{R}{Max} \quad \varepsilon(1-R) + \frac{\varepsilon^{\rho}}{1+r}(1+R^{\alpha}) - cR + \lambda\left[\mu\varepsilon(1-R) - cR\right], \tag{14}$$

The constraint binds for any ε if and only if

$$\mu < \underline{\mu} = \frac{cR^{**}\left(\varepsilon^h\right)}{\varepsilon^h\left(1 - R^{**}\left(\varepsilon^h\right)\right)}, \text{ where } R^{**}\left(\varepsilon^h\right) = \left[\frac{\alpha\left(\varepsilon^h\right)^\rho}{(1+r)\left(\varepsilon^h + c\right)}\right]^{\frac{1}{1-\alpha}}, \tag{15}$$

and does not bind for any ε if and only if

$$\mu > \overline{\mu} = \frac{cR^{**}\left(\varepsilon^l\right)}{\varepsilon^l\left(1 - R^{**}\left(\varepsilon^l\right)\right)}, \text{ where } R^{**}\left(\varepsilon^l\right) = \left[\frac{\alpha\left(\varepsilon^l\right)^\rho}{(1+r)\left(\varepsilon^l + c\right)}\right]^{\frac{1}{1-\alpha}}, \tag{16}$$

Innovation and output under binding constraint are:

$$R^* = \frac{\mu\varepsilon}{c + \mu\varepsilon}, \quad Y^* = \frac{c\varepsilon}{c + \mu\varepsilon} + \varepsilon \tag{17}$$

Apparently, $\frac{dR^*}{d\varepsilon} > 0$ $\frac{dY^*}{d\varepsilon} > 0$: R^* and Y^* commove positively in response to ε, consistent with Proposition 3. Moreover, (17) suggests that $\frac{dR^*}{d\mu} > 0$; it can also be proven that $R^* < R^{**}$; thus, R is weakly increasing in μ, consistent with Propositions 4.

Figure 1 plots the optimal innovation corresponding to five different μ values. The figure is generated assuming $\rho = 0.6$, $\alpha = 0.75$, $r = 0.05$, $c = 0.5$, $\varepsilon^l = \exp(-0.14)$ and $\varepsilon^h = \exp(0.14)$. Correspondingly, $\underline{\mu} = 0.0278$ and $\overline{\mu} = 0.0454$. The parameterization satisfies Assumptions 1 as well as $\rho < \frac{\varepsilon}{\varepsilon + c}$ for any ε, implying counter-cyclical innovation under complete financial market.

Panel 1 of Figure 1 plots innovation against ε. The solid line indicates R^{**} with $\mu > \overline{\mu}$. The dotted line at the bottom indicates R^* with $\mu < \underline{\mu}$; the dotted line at a higher position refers to R^* with $\mu = \underline{\mu}$. Apparently, R^{**} declines in ε, but R^* rises in ε. Panel 2 plots innovation against output. Since our parameterization ensures that ε raises Y, the relationship between innovation and output resembles that between innovation and ε. In both panels, higher μ raises the dotted line to a higher position, implying a positive impact of μ on innovation under binding constraints.

Interestingly, as μ rises to a value above $\underline{\mu}$ but below $\overline{\mu}$, the cyclicality of innovation

displays an asymmetry. This is shown in Figure 1 as the dashed lines that meet the solid line at some threshold $\overline{\varepsilon}$ in panel 1 and at $\overline{Y}$ in panel 2. In this case, the constraint binds for $Y < \overline{Y}$ and doe not bind for $Y > \overline{Y}$, so that innovation is pro-cyclical for $Y < \overline{Y}$ and counter-cyclical for $Y > \overline{Y}$. With higher μ, the position of the binding range of the dashed line moves higher, $\overline{Y}$ lowers, and the innovation is pro-cyclical for a smaller value range of output.[2]

To see how financial-market frictions hinder potential virtue of bad times, suppose that $\mu \in \left(\underline{\mu}, \overline{\mu}\right)$ and output is initially above $\overline{Y}$. When a negative shock drives Y below $\overline{Y}$, innovation would move somewhere on the dashed line due to binding constraints, although the optimal innovation would have been on the solid line if the financial market were complete. Hence, the distance between the dashed line and the solid line indicates the potential virtue of bad times hindered by financial-market frictions.

4 R&D's Cyclicality and Industry Financial Strength

This section applies our theory to data. In particular, we examine the cyclicality of R&D, namely, the comovement between R&D and output, using an industry panel of R&D, output, and finance from the U.S. manufacturing sector. The idea is to take advantage of the fact that industry cycles are not perfectly synchronized, due to either industry-specific shocks or industry-specific responses to common aggregate shocks (Ouyang, 2009).

4.1 Data

Three data sources are combined to construct our industry panel. R&D by industry is from the National Science Foundation (NSF) that publishes annual data on R&D expenditure

[2] The asymmetry in the cyclicality of innovation with $\mu \in \left(\underline{\mu}, \overline{\mu}\right)$ is consistent with Ouyang (2009), who estimates that demand shocks cause asymmetric response in R&D. She reports that a demand shock, either positive or negative, reduces R&D always. To see how this can be captured in Figure 1, suppose that output is initially at $\overline{Y}$. Then, an ε shock would cause innovation to respond asymmetrically: higher ε raises output, but lowers innovation by raising innovation's opportunity cost; lower ε reduces both output and innovation by tightening the binding constraint.

for major manufacturing industries from 1958 to 1998 based on the 1987 Standard Industry Classification (SIC) system.[3] Data on output are taken from the NBER manufacturing productivity (MP) database that provides annual data on production from 1958 to 2002 for 469 four-digit manufacturing industries. Data on industry finance are from the Quarterly Financial Report (QFR) published by Bureau of the Census, who presents the income statements and the balance sheets for major manufacturing industries.

Ideally we would like to have R&D data for all 469 industries. Unfortunately, the R&D data is available only for 20 major industries at the two-digit or the combination of three-digit SIC level, out of which 16 are covered by the QFR. The MP data is aggregated according to the definitions of R&D industries. These 16 industries, together with their detailed SIC codes, are listed in the first two columns of Table 1. This gives us a panel of R&D and output for 16 manufacturing industries from 1958 to 1998.

We use real company-financed R&D expenditure to measure innovation.[4] The nominal R&D series are converted into 2000 dollars using the GDP deflator, following Barlevy (2007). Output is measured as real value added, as the deflated value added using shipment-value-weighted price deflator. We use two measures provided by the QFR to indicate industry financial strength: liquid assets (cash and U.S. government securities), which can be used to finance R&D internally, and net worth, which can be used as collateral for borrowing externally. Because the full panel of financial indicators are not readily available, the quarterly average of each indicator in 1960, 1970, 1980, 1990, and 2000 are calculated to assess the sample industries' financial strength over the entire 1958-1998 sample period.[5] More specifically, μ is measured as $\frac{mean(\kappa)}{mean(y)}$, where κ denotes the value of net worth or liquid assets in 2000 dollars, $mean\,(\kappa)$ is the the quarterly average of κ for years 1960, 1970, 1980, 1990,

[3] After 1998, R&D by industry is published based on the North American Industry Classification System.

[4] Some industry-year observations in the R&D panel are suppressed to avoid disclosure of individual firms' operations. Following Shea (1998), the growth of total R&D including both company-financed and federal-financed is used to interpolate gaps in the series of company-financed R&D. There are three cases where the observations on the total R&D spending are also missing, we use growth in company-financed R&D at higher SIC level for interpolation.

[5] The QFR are not available in electronic format until 1987.

and 2000, and $mean(y)$ is the time-series average of annual real value added from 1958 to 1998. When measured as the liquid-asset-over-output ratio, μ indicates an industry's ability to finance R&D internally; when measured as the net-worth-over-output ratio, it represents an industry's ability to finance R&D through external borrowing.

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 use log-first differences (growth rates) in R&D and output when examining the cyclicality of R&D.

4.2 Baseline Cyclicality of R&D

Table 1 summarizes the baseline cyclicality of R&D. Column three of Table 1 presents the time-series correlation coefficients between R&D growth and output growth for 16 sample industries from 1958 to 1998. Out of the 16 coefficients, five are negative and 11 are positive. Pooling industries together gives an average correlation coefficient of 0.0784.

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

$$\triangle \ln R_{it} = \beta_0 + \beta_1 \triangle \ln Y_{it} + \epsilon_{it}. \tag{18}$$

$\triangle \ln R_{it}$ indicates the R&D growth for industry i in year t; $\triangle \ln Y_{it}$ is the output growth; and ϵ_{it} is the error. (18) examines the contemporaneous relationship between R&D growth and output growth only, as the results with additional output lags are quantitatively similar. Our results also remain robust to including a post-1992 dummy and quadratic time trends before and after 1980 as additional controls following Ouyang (2009). All results are available upon

request.

The estimation results of (18) are listed in Column four of Table 1: five out of the 16 estimates are negative, only one statistically significant. 11 are positive, out of which five are statistically significant. Pooling industries together produces an estimate around 0.1090, significant at 5% level.

The conventional theory on the virtue of bad times predicts R&D to be concentrated when output is low. Table 1 provides little support for such theory. Instead, it shows that R&D is pro-cyclical on average and, more importantly, the cyclicality of R&D differs significantly across industries.

4.3 Industry Financial Strength: cross-section evidence

We explore whether financial market frictions help to explain the cross-industry differences in R&D's cyclicality. If binding financial constraint is what causes the contradiction between the conventional theory and the data, industry financial strength should affect both the cyclicality and the level of R&D: in particular, R&D is counter-cyclical for industries with sufficiently high μ, but pro-cyclical for industries with sufficiently low μ, and displays mixed cyclicality with μ whose value lies in the middle; moreover, the R&D level rises in μ cross-section.

4.3.1 Petroleum Refining

Table 2 presents the approximated μ values for 16 sample industries, in the order of their rank in the net-worth ratio. Apparently, Petroleum Refining (SIC 29) shows superior financial strength by both indicators. Its liquid-asset ratio equals 0.7860, almost three times of that for Drugs (SIC 283) that has the second highest liquid-asset ratio; its net-worth ratio equals 9.7762, almost five times of that of Electronics (SIC 36) that has the second highest net-worth ratio. As a comparison, the liquid-asset ratio and the net-worth ratio average 0.1762 and 0.7567 only for the entire sample. Figure 2 presents the histograms of two approximated

μ values, reinforcing this impression: the observation on the far right captures the μ values for Petroleum Refining (SIC 29), which are well above those of other industries.

Most interestingly, in Table 1 Petroleum Refining (SIC 29) is also the only industry that features counter-cyclical R&D: the time-series correlation coefficient between Petroleum output growth and Petroleum R&D growth is -0.3144; the OLS estimates show that a 10% increase in Petroleum output growth is associated with about 1.74% decrease in Petroleum R&D growth, significant at 5% level. Figure 3 presents the time-series plots of R&D growth and output growth for Petroleum Refining from 1958 to 1998: the two curves display negative comovement over time, suggesting that Petroleum Refining R&D is counter-cyclical.

The counter-cyclicality of Petroleum Refining R&D is probably the first piece of evidence in the literature consistent with the conventional theory on the virtue of bad times. Why Petroleum Refining R&D co-moves negatively with its output, unlike other industries, is an interesting phenomenon, and may intrigue different explanations.

For example, one may argue that Petroleum Refining could be a counter-cyclical industry over the aggregate cycle, possibly due to fluctuations in oil prices. However, it is hard to argue theoretically why oil-price shocks influence the cyclicality of R&D differently as they raise the production cost, lower the production profit, and thus reduce the opportunity cost of R&D. Moreover, our data shows that Petroleum Refining output growth co-moves positively with real GDP growth with a time-series correlation coefficient of 0.4159, just like most of the other industries.[6]

Moreover, one may argue that counter-cyclical R&D does not necessarily suggest that R&D responds negatively to production shocks. According to our theory, $\frac{dY}{d\varepsilon} = f(1-R) + f(1) - \varepsilon f'(1-R)\frac{dR}{d\varepsilon}$. Hence, there are two cases in which R&D appears counter-cyclical. $\frac{dR^{**}}{d\varepsilon} < 0$ and $\frac{dY}{d\varepsilon} > 0$ is the case with the virtue of bad times. Another case is $\frac{dR^{**}}{d\varepsilon} > 0$ and $\frac{dY}{d\varepsilon} < 0$ with $f(1-R) + f(1) < \varepsilon f'(1-R)\left|\frac{dR}{d\varepsilon}\right|$: a positive production shock raises R&D by so much that output declines. However, the literature has provided little evidence

[6] As a matter of fact, the only industry in our panel that moves against the aggregate cycle is Food (SIC 20): its time-series correlation coefficient with real GDP growth is -0.0289.

suggesting that positive production shocks actually reduce output. Moreover, our data show that R is very small quantitatively for all industries including Petroleum Refining: annual real Petroleum Refining R&D spending averages 20.78 million in 2000 dollars from 1958 to 1998, only 0.64% of its 1958-1998 average annual real investment of 3.22 billion. Sufficiently small R makes it unlikely for $f(1-R)+f(1)<\varepsilon f'(1-R)\left|\frac{dR}{d\varepsilon}\right|$ to hold.

Nonetheless, Table 2 suggests one reasonable explanation based on our theory for counter-cyclical Petroleum Refining R&D, presenting this industry's superior financial strength: with sufficiently high μ and thus non-binding financial constraint, entrepreneur are able to concentrate R&D when its opportunity cost as forgone output is low. This points to the possibility that the conventional theory does capture the key factor in determining innovation's cyclicality. In other words, bad times do have virtue in boosting innovation for long-run growth, at least for Petroleum Refining.

4.3.2 Pro-cyclical R&D

According to Table 1, R&D is pro-cyclical for five industries with significant positive estimates: Rubber (SIC 30), Stones(SIC 32), Electronics (SIC 36), Aerospace (SIC 372, 376), and Instruments (SIC 38). To examine how industry financial strength affects the probability of industry R&D's being pro-cyclical, we estimate the following linear probability model (LPM) and probit model :

$$\begin{aligned} P\left(pro_i=1|\mu,\widehat{\rho}\right) &= \beta_0+\beta_1\mu_i+\beta_2\widehat{\rho}_i+\epsilon_i \\ P\left(pro_i=1|\mu,\widehat{\rho}\right) &= \Phi\left(\beta_0+\beta_1\mu_i+\beta_2\widehat{\rho}_i\right). \end{aligned} \tag{19}$$

pro_i equals one for Stones, Rubber, Electronics, Aerospace, and Instruments and equals zero for all other industries. Φ is the standard normal distribution function $\widehat{\rho}_i$ is an additional control.

We control for $\widehat{\rho}_i$ because μ_i is not the only factor determining R&D' cyclicality. Ac-

cording to our theory, the expected future productivity equals ε^{ρ}, where ρ is the elasticity of ε^{ρ} with respect to ε. Thus, ρ captures how responsive the expected future profitability is to present shock or, alternatively, the magnitude of the cyclicality of the marginal expected future return. Intuitively, sufficiently high ρ makes it more likely for the cyclicality of the marginal return to R&D to dominate, so that R&D is pro-cyclical even with non-binding constraint. This is shown in Section 3 as that R^{**} is pro-cyclical when $\rho > \frac{\varepsilon}{\varepsilon+c}$.

Since ρ is not directly observable, we estimate ρ using data on the five-factor total factor productivity (TFP) growth. More specifically,

$$\triangle \ln \varepsilon_{it} = \rho_i \triangle \ln \varepsilon_{it-1} + \zeta_i \ln R_i + \epsilon_{it}. \tag{20}$$

$\triangle \ln \varepsilon_{it}$ is the TFP growth for industry i in year t. $\ln R_i$ is the time-series average of real R&D spending in log level for industry i. We include $\ln R_i$ in the regression to control for the influence of past innovation on endogenous productivity growth. Ideally, such influence should be controlled for using lagged R&D. However, it is hard to determine the appropriate lag length for R&D to impact productivity: some research projects may take over twenty years to influence production, while some others can generate prompt productivity gain. Moreover, longer lag length reduces the sample size. Therefore, we use $\ln R_i$ instead to control for average endogenous productivity growth driven by innovation.

(20) is estimated for each of the sample industries; the estimated ρ_i therefore reflects the 1958-1998 average persistence in productivity for industry i, controlling for industry R&D level. Table 3 summarizes the estimated ρ_i's in Column two and the estimated ζ_i's in Column three. Pooling all industries together produces an average annual persistence of 0.1353, significant at 5% level.[7] The results stay robust to replacing the average log level of R&D by the average growth in R&D or by a constant. All our results employing $\widehat{\rho}_i$'s stay robust

[7]Note that the estimated persistence at the industry level is smaller than that at the aggregate level documented by the literature. This should not be surprising as it has been established theoretically and empirically that cross-industry comovement contributes significantly to the aggregate cycle, and therefore amplifies the aggregate persistence (Long and Plosser, 1983; Shea, 2002).

to replacing insignificant $\widehat{\rho_i}$'s with zeros or estimating $\widehat{\rho_i}$'s using the output growth instead of the TFP growth.[8]

Accordingly, we estimate (19) with μ measured as the net-worth ratio, as the liquid-asset ratio, with and without $\widehat{\rho_i}$. The estimate on β_1 reflects the impact of μ on the probability of industry R&D's being pro-cyclical. The sample size is 16. Table 4 summarizes the results. The eight estimates on β_1 are all negative. Without controlling for $\widehat{\rho_i}$, only one estimate is statistically significant. After controlling for $\widehat{\rho_i}$, the four estimates all become statistically significant with bigger point estimates. These results are robust to leaving Petroleum Refining out of the sample. In summary, Table 4 suggests a negative relationship between industry financial strength and the probability of industry R&D's being procyclical. According to our theory, it can be explained as that lower μ are more likely to cause binding financial constraints that causes pro-cyclical R&D.

4.3.3 The R&D level

To further confirm the impact of binding financial constraint on industry R&D, we apply to our panel Proposition 4 that predicts the level of R&D to increase in μ: with binding constraint, higher μ relaxes the constraints and makes higher R&D spending feasible; with non-binding constraint, μ has no impact on the level of R&D. Accordingly, we estimate the following:

$$\ln R_i = \alpha_0 + \alpha_1 \mu_i + \alpha_2 \ln Y_i + \varepsilon_i. \tag{21}$$

$\ln R_i$ and $\ln Y_i$ are the time-series averages of real R&D spending and output in log levels for industry i. The sample size is 16. $\alpha_1 > 0$ under the null. We include $\ln Y_i$ to control for the industry size: for example, L is taken as constant in our theory, but it differs across industries in practice. We estimate (21) with and without Petroleum Refining.

[8] There are both advantages and disadvantages of estimating cyclical persistence using the TFP growth or the output growth. For example, demand shocks, as an important force for the production cycle, may not be reflected in the TFP growth. The output growth incorporates demand shocks; but the estimated persistence in the output growth may be driven by input adjustment cost instead of the demand persistence itself.

Our results are summarized in Table 5. The estimated coefficients on μ_i are all positive and statistically significant at 5% level or above, either with μ approximated as the net-worth ratio or as the liquid-asset ratio, and either with or without Petroleum Refining. In particular, a 10% higher net-worth ratio is associated with 2.0% higher R&D spending for the full sample, and with 13.4% higher R&D spending for industries other than Petroleum Refining; a 10% higher liquid-asset ratio is associated with 29.0% higher R&D spending for the full sample, and with 105.4% higher R&D spending for industries other than Petroleum Refining. The bigger point estimates when Petroleum Refining is excluded from the estimation is consistent with Proposition 4, as the R&D level strictly rises in μ only for industries with binding constraint.

4.4 Industry financial strength: panel evidence

Note that our cross-section evidence is based on 16 observations only due to limited data availability. To test our theory with more observations and higher degrees of freedom, we run the following panel regression to examine the impact of industry financial strength on the cyclicality of R&D:

$$\triangle \ln R_{it} = \beta_0 + \beta_1 \triangle \ln Y_{it} + \beta_2 \mu_i \triangle \ln Y_{it} + \beta_3 \widehat{\rho}_i \triangle \ln Y_{it} + \epsilon_{it}. \tag{22}$$

Compared to (18), (22) includes two additional interaction terms: $\mu_i \triangle \ln Y_{it}$ and $\widehat{\rho}_i \triangle \ln Y_{it}$. β_2 captures an additional influence of μ_i on R&D's cyclicality. Industry R&D is pro-cyclical on average according to Table 1. If binding constraints contribute to such procyclicality. Then higher μ_i should reduce R&D's procyclicality by relaxing the binding constraint. Therefore, $\beta_2 < 0$ under the null. Similarly, β_3 reflects an additional impact of $\widehat{\rho}_i$ on R&D's cyclicality. Higher $\widehat{\rho}_i$ drives the marginal expected future return more responsive to present shocks, so that R&D is more likely to be pro-cyclical. Hence, $\beta_3 > 0$ under the null.

Alternatively, $\mu_i \triangle \ln Y_{it}$ and $\widehat{\rho}_i \triangle \ln Y_{it}$ can be interpreted as follows. Because μ_i is the

financial resource as a fraction of output, $\mu_i \triangle \ln Y_{it}$ stands for growth in financial resources over the production cycle. Since $\widehat{\rho_i}$ is the persistence in the cyclical shock, $\widehat{\rho_i} \triangle \ln Y_{it}$ represents the expected future profitability based on current profitability.[9] Intuitively, (22) estimates the cyclicality of R&D and how industry financial strength affects such cyclicality, controlling for the expected future profitability.

We estimate (22) with μ_i approximated as the net-worth ratio and as the liquid-asset ratio. Our results are summarized in Column two of Table 6. The estimated β_1's are both positive and significant at 5% level, suggesting that industry R&D is pro-cyclical on average. The estimated β_2's are both negative and significant at 1% level, suggesting that higher μ reduces such pro-cyclicality. In particular, a 10% increase in output growth is associated with about 2.2% increase in R&D growth; but such pro-cyclicality is reduced by 0.5% with higher net-worth ratio, and by 6.3% with higher liquid-asset ratio. The estimated β_3's are both positive and significant at 5% level, consistent with the null.

However, several cautionary remarks should be made. First, it is possible that the negative estimates on β_2 comes entirely from Petroleum Refining: if this is true, then the results in Column two of Table 6 are just a simple replication of the cross-section evidence. Secondly, our theory suggests that μ affects the *possibility* of R&D's being procyclical; but, conditional on R&D's being pro-cyclical, it is hard to tell how μ affects the estimated output coefficient. As a matter of fact, (11) and (12) suggest that μ's impact on the estimated output coefficient conditional on binding constraint can be positive, depending on the specific functional form of $c(R)$.[10] In the example presented in Section 3, Figure 1 shows that the slope is higher with higher μ between the two lines at the bottom displaying pro-cyclical R&D with binding constraint,

More interestingly, industry financial strength should contribute to the mixed cyclicality

[9] One may argue that $\widehat{\rho_i}$ is the annual persistence, but the return to R&D usually takes longer than a year to realize. Nonetheless, persistence over five-year, ten-year, or twenty-year horizon is still based on the persistence over one year, so that β_3 still qualitatively captues the influence of the expected future return to R&D.

[10] Combining (11) and (12) suggests that, in response to ε, $\frac{dR}{dY} = \frac{\mu f}{fc' + f(1)c' + f(1)\mu\varepsilon f'}$.

of R&D for industries whose *R&D* appears acyclical. This is shown in Figure 1: with $\mu \in (\underline{\mu}, \overline{\mu})$, innovation is pro-cyclical when output is low and when the constraint binds, and is counter-cyclical when output is high and when the constraint does not bind; lower μ enlarges the output range within which the constraint binds. Intuitively, higher μ *makes R&D co-moving with output positively less often* for industries whose R&D displays mixed cyclicality. This is an interesting pattern that cannot be captured by the cross-section evidence.

Accordingly, we re-estimate (22), allowing β_2 to differ for industries with pro-cyclical R&D, acyclical R&D, and counter-cyclical R&D based on Table 1. More specifically:

$$\begin{aligned} \triangle \ln R_{it} &= \beta_0 + \beta_1 \triangle \ln Y_{it} + \beta_2^{pro} \mu_i \triangle \ln Y_{it} D^{pro} + \beta_2^{acy} \mu_i \triangle \ln Y_{it} D^{acy} + \beta_2^{cou} \mu_i \triangle \ln Y_{it} D^{cou} \\ &\quad + \beta_3 \widehat{\rho}_i \triangle \ln Y_{it} + \epsilon_{it}, \end{aligned} \tag{23}$$

where D^{pro}, D^{acy} and D^{cou} are dummy variables indicating industry R&D's being pro-cyclical, acyclical, and counter-cyclical. Based on Table 1, D^{pro} equals one for Rubber, Stones, Electronics, Aerospace, and Instruments; D^{cou} equals one for Petroleum Refining, and D^{acy} equals one for the other 11 industries. Under the null, $\beta_2^{acy} < 0$ and $\beta_2^{cou} < 0$.

We estimate (23) with μ measured as the net-worth ratio and as the liquid-asset ratio. Our results are summarized in Columns three, four, and five of Table 6. Apparently, the two estimates on β_2^{cou} are both negative and significant at 1% level, showing that Petroleum Refining R&D's being counter-cyclical can be explained by its high μ. The two estimates on β_2^{pro} are both statistically insignificant. Most interestingly, the two estimates on β_2^{acy} are both negative, one significant at 1% level and the other significant at 5% level, implying that R&D is less likely to co-move positively with output with high μ or, alternatively, that μ value contributes to the mixed cyclicality for industries with acyclical R&D. These results suggest that the negative estimates on β_2 listed in Column two of Table 6 comes not only from Petroleum Refining, but also from industries whose R&D display mixed cyclicality.

In summary, Table 6 suggest the following. Industry R&D is pro-cyclical on average, but stronger financial strength dampens such pro-cyclicality. This is consistent with our null, and points to the possibility that binding financial constraint is a key factor causing the contradiction between the conventional theory and data. In other words, the potential virtue of bad times does exist potentially, but is hindered by financial-market frictions.

5 Conclusion

We revisit the virtue of bad times theoretically and empirically. Our theory suggests that whether bad times have virtue relies on the magnitude of the cyclicality of innovation's marginal opportunity cost relative to that of its marginal return. However, even if bad times do possess potential virtue, financial-market frictions can hinder such virtue, preventing innovation from rising during recessions.

We carry our theory to an industry panel, and find evidence consistent with its predictions. The cross-section evidence suggests that stronger industry financial strength is associated with higher R&D level as well as a smaller probability of having pro-cyclical R&D; Petroleum Refining, which displays superior financial strength relative to the rest of the sample, is also the only industry with counter-cyclical R&D as the conventional theory predicts. Our panel evidence further suggests that industry financial strength contributes to the mixed cyclicality of R&D for industries whose R&D appear acyclical.

Future theoretical research should investigate factors determining the cyclicality of innovation's opportunity cost relative to that of its expected return or, alternatively, conditions under which bad times indeed possess potential virtue. Future empirical research should improve on data availability on R&D and finance at the industry or aggregate level to further explore the relationship between the virtue of bad times and financial-market frictions.[11]

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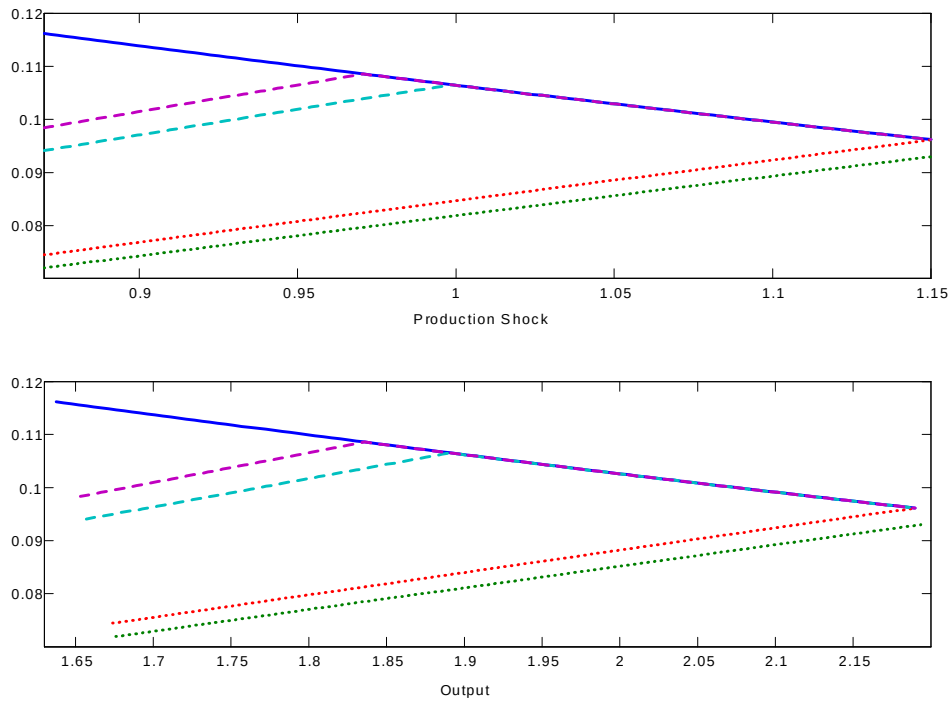

Figure 1: Innovation and Production corresponding to different μ: the four lines in each panel corresponds to, from bottom to top, $\mu = 0.0268$, $\mu = 0.0278$, $\mu = 0.0358$, $\mu = 0.0376$, and $\mu = 0.0454$. Upper panel plots innovation against production shock ε; lower panel plots innovation against output. The figure is generated assuming $\rho = 0.6$, $\alpha = 0.75$, $r = 0.05$, $c = 0.5$, $\varepsilon^l = \exp(-0.14)$ and $\varepsilon^h = \exp(0.14)$. See text for more details.

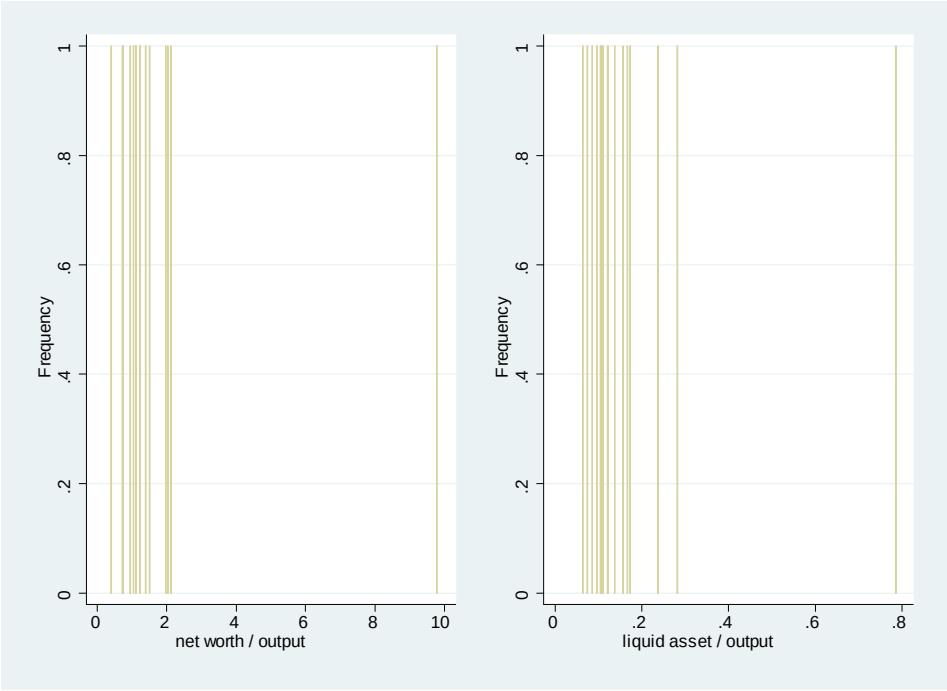

Figure 2: Sample distribution of μ across 16 industries. Each bin is an industry. μ is approximated as the net-worth ratio in the left panel and as the liquid-asset ratio in the right panel. The net-worth ratio is calculated as the quarterly average of an industry's net worth value in 2000 dollars for years 1960, 1970, 1980, 1990, and 2000 over the time-series average of an industry's annual real value added from 1958 yo 1998. The liquid-asset ratio is calculated as an industry's liquid asset value in 2000 dollars for years 1960, 1970, 1980, 1990, and 2000 over the time-series average of an industry's real value added from 1958 to 1998. The bin with the highest μ value is Petroleum Refining (SIC29) in either panel. Data on net worth and liquid assets are from the Quarterly Financial Reports published by the Census of Bureau. Data on output is from the NBER manufacturing productivity database. See text for more details.

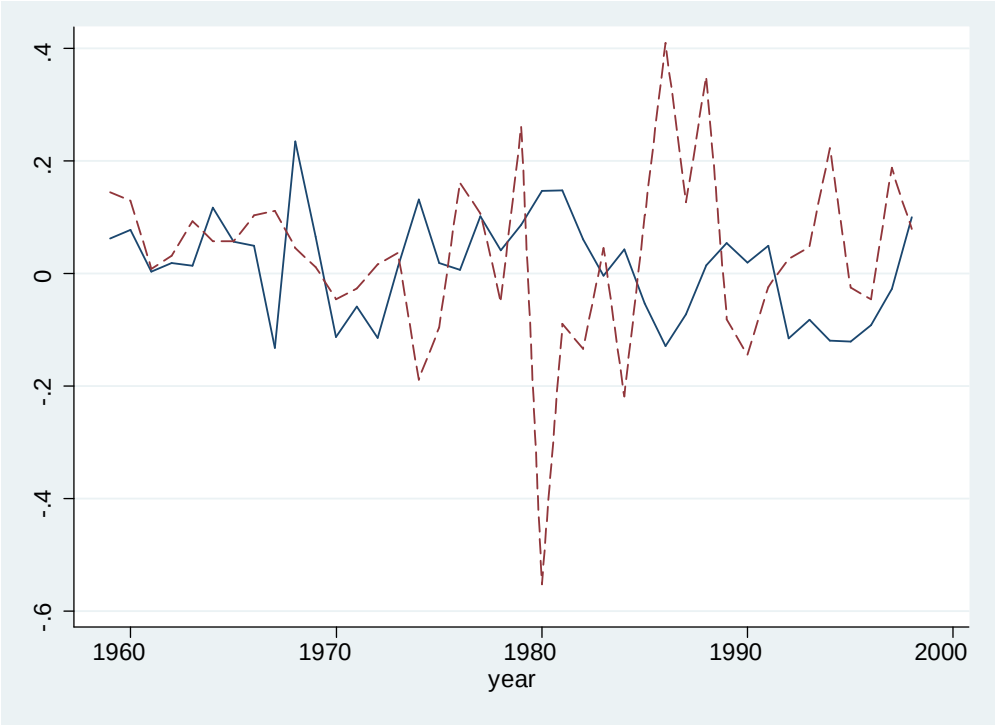

Figure 3: The R&D growth and output growth for Petroleum Refining (SIC 29) from 1958 to 1998. The solid line indicates R&D growth and the dashed line indicates output growth. Data on R&D are from the NSF and data on output are from the NBER Manufacturing Productivity databases. See text for more details.

Industry	**1987 SIC**	**Corr**(R_t,Y_t)	$\widehat{\beta_1}$
Food	20, 21	0.0741	0.1499
Lumber	24,25	0.0193	0.0764
Paper	26	−0.0787	−0.1785
Industry Chemicals	281,282, 286	−0.1069	−0.0775
Drugs	284	0.2243	0.2992
Other Chemicals	284, 285, 287, 289	−0.1501	−0.3515
Petroleum	29	−0.3144	−0.1744***
Rubber	30	0.1866	0.3384**
Stones	32	0.3208	0.6298**
Furrous Metals	331, 332, 339	0.0327	0.0355
Non-Ferrous Metals	333, 334, 335, 336	−0.0690	−0.0974
Metal Products	34	0.1050	0.1743
Machinery	35	0.1627	0.2214
Electronics	36	0.5638	0.4143***
Aerospace	372, 376	0.3736	0.5197***
Instruments	38	0.2771	0.2883*
average		**0.0784**	**0.1090****

Table 1: Baseline cyclicality of industry R&D. corr(R,Y) is the time-series correlation between R&D growth and output growth from 1958 to 1998; $\widehat{\beta_1}$ is the OLS estimate on output growth by regressing R&D growth on a constant and output growth; * indicates significance at 10% level. ** indicates significance at 5% level. *** indicates significance at 1% level. Data on R&D growth are from the National Science Foundation; data on output growth are from the NBER manufacturing productivity database. See text for more details.

Industry	**liquid assets/Output**	**Net worth/Output**
Petroleum	0.7860	9.7762
Electronics	0.2367	2.1252
Drugs	0.2820	2.0355
Non-Ferrous Metals	0.1559	1.9652
Industry Chemicals	0.1041	1.5057
Instruments	0.1217	1.3971
Paper	0.0852	1.2401
Other Chemicals	0.1728	1.2347
Machinery	0.1373	1.1173
Furrous Metals	0.1658	1.1034
Stone	0.1211	1.0437
Food	0.1100	0.9485
Aerospace	0.1067	0.7442
Rubber	0.0744	0.7405
Metal Products	0.0957	0.7261
Lumber	0.0638	0.4040
Average	0.1762	0.7567

Table 2: Industry financial strength. The net-worth ratio is calculated as the quarterly average of an industry's net worth value in 2000 dollars for years 1960, 1970, 1980, 1990, and 2000 over the time-series average of an industry's annual real value added from 1958 yo 1998. The liquid-asset ratio is calculated as an industry's liquid asset value in 2000 dollars for years 1960, 1970, 1980, 1990, and 2000 over the time-series average of an industry's real value added from 1958 to 1998. Industries are ranked according to the value of their net-worth ratio. Data on liquid assets and net worth are from the Quarterly Financial Reports published by the Census of Bureau. Data on output are from the NBER manufacturing productivity database. See text for details.

Industry	$\widehat{\rho_i}$	$\widehat{\zeta_i}$
Food	-0.3460^{**}	0.0018^{**}
Lumber	0.0675	0.0049
Paper	-0.1255	0.0016
Industry Chemicals	0.1205	0.0020
Drugs	0.4412^{***}	0.0001
Other Chemicals	-0.1176	0.0024
Petroleum	0.1336	0.0018
Rubber	-0.0835	0.0060^{**}
Stones	0.1413	0.0031
Furrous Metals	-0.0206	0.0036
Non-Ferrous Metals	0.0426	0.0023
Metal Products	-0.0170	0.0016
Machinery	0.2346	0.0033
Electronics	0.4193^{**}	0.0031^{**}
Aerospace	-0.1529	0.0003
Instruments	0.2289	0.0010
average	0.1351^{**}	0.0023^{***}

Table 3: Persistence in industry productivity. The OLS estimation results of regressing industry TFP growth on one-year lagged TFP growth and industry average real R&D spending in log levels. The sample size of each regression is 39. $\widehat{\rho_i}$ is the estimated coefficient on lagged TFP growth for industry i; $\widehat{\zeta_i}$ is the estimated coefficient on log real R&D level for industry i. * indicates significance at 10% level. ** indicates significance at 5% level. *** indicates significance at 1% level. See text for more details.

	LPM	**Probit**	**LPM**	**Probit**
	no control		**controlling for $\widehat{\rho}$**	
μ as **net-worth ratio**	-0.0417^{*}	-0.3428	-0.0530^{**}	-0.5406^{*}
	(0.0206)	(0.2665)	(0.0231)	(0.2972)
Log-likelihood	-	-9.4874	-	-8.7869
Pseudo R-squared	0.0365	0.0460	0.4918	0.1341
μ as **liquid-asset ratio**	-0.4582	-2.8649	-0.6590^{*}	-4.4013^{*}
	(0.3066)	(1.9855)	(0.4930)	(2.6744)
Log-likelihood	-	-9.6810	-	-9.0441
Pseudo R-squared	0.0273	0.0296	0.0805	0.0910

Table 4: LPM and Probit Estimations of the impact of μ on industry R&D's being pro-cyclical. 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 number of observations is 16. Robust standard errors are in parentheses. The Pseudo R-squared for the LPM is just the usual R-quared for OLS; the Pseudo R-squared for probit is calcuated according to Wooldrige (2002). See notes to Tables 1, 2 and 3 for data sources; see text for more details.

	With SIC 29		**Without SIC 29**	
μ **as net-worth ratio**	0.2036** (0.0900)	-	1.3487** (0.4592)	-
μ **as liquid-asset ratio**	-	2.9004** (1.2123)	-	10.5443*** (2.7835)
$\ln \mathbf{Y}$	1.1155** (0.5175)	1.1426** (0.4529)	1.2325** (0.4165)	1.1399*** (0.3328)
R-squared	0.2892	0.3226	0.5282	0.4844

Table 5: The R&D level and industry financial strength: the OLS results of $lnR_i = \alpha_0 + \alpha_1\mu_i + \alpha_2 \ln Y_i + \varepsilon_i$. lnR_i is the time-series average of real R&D spending in log level for industry i; μ_i is the financial indicator; lnY_i is the time-series average of industry output in log level for industry i. SIC 29 refers to the industry of Petroleum Refining. The sample size is 16 with Petroleum Refining and 15 without Petroleum Refining. Robust standard errors are in parentheses. ** indicates significance at 5% level. *** indicates significance at 1% level. See notes to Tables 1 and 2 for data sources. See text for more details.

μ as net-worth ratio	**full sample** # of obs: 640	$D^{\mathbf{cou}}=\mathbf{1}$ # of obs:40	$D^{\mathbf{acy}}=\mathbf{1}$ # of obs:440	$D^{\mathbf{pro}}=\mathbf{1}$ # of obs: 160
$\triangle \ln \mathbf{Y}_{it}$	0.2145** (0.0816)	0.4377*** (0.1122)		
$\boldsymbol{\mu}_i \triangle \ln \mathbf{Y}_{it}$	−0.0504*** (0.0062)	−.0736*** (0.0121)	−0.2822*** (0.0800)	−0.1375 (0.0895)
$\widehat{\rho}_i \triangle \ln \mathbf{Y}_{it}$	0.5625** (0.2523)	0.6956* (0.3415)		
R-sqared	0.0256	0.0324		
μ liquid-asset ratio	**full sample** # of obs: 640	$D^{\mathbf{cou}}=\mathbf{1}$ # of obs:40	$D^{\mathbf{acy}}=\mathbf{1}$ # of obs:440	$D^{\mathbf{pro}}=\mathbf{1}$ # of obs: 160
$\triangle \ln \mathbf{Y}_{it}$	0.2328** (0.0884)	0.4131*** (0.1388)		
$\boldsymbol{\mu}_i \triangle \ln \mathbf{Y}_{it}$	−0.6329*** (0.0960)	−0.7986*** (0.2151)	−2.5542** (0.8831)	−0.3253 (1.0874)
$\widehat{\rho}_i \triangle \ln \mathbf{Y}_{it}$	0.5910** (0.2632)	0.2098 (0.3426)		
R-sqared	0.0241	0.0281		

Table 6: R&D's cyclicality and industry financial strength: the OLS results of regressing R&D growth on a constant, output growth, and the interaction of μ_i and output growth, and the interaction of $\widehat{\rho}_i$ and output growth. The sample size is 640. $\triangle \ln Y_{it}$ is the output growth for industry i in year t. $\widehat{\rho}_i$ is from Table 3. Based on Table 1, $D^{cou} = 1$ indicates industry with counter-cyclical R&D (Petroleum Refining); $D^{acy} = 1$ indicates industries with acyclical R&D; $D^{pro} = 1$ indicates industries with pro-cyclical R&D. Robust standard errors clustered by industry are in parentheses. * indicates significance at 10% level. ** indicates significance at 5% level. *** indicates significance at 1% level. See notes to Tables 1, 2 and 3 for data sources. See text for more details.