# The Symmetry and Cyclicality of R&D Spending in Advanced Economies*

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**Abstract**

This paper explores the impact of cyclical macroeconomic fluctuations on corporate R&D spending. Most existing studies are conducted at the industry or firm level and find procyclical corporate R&D. Some of these studies also provide evidence suggesting credit constraints play an important role in explaining the cyclical behavior of R&D. Our analysis of the relationship between GDP, credit, and R&D begins with a theoretical model that allows for the possibility of credit constraints. We then turn to an empirical analysis of a panel of 22 advanced economies. Our most robust empirical finding is that R&D is symmetrically procyclical even after controlling for credit market conditions. We conclude that credit market conditions are not sufficient to fully explain the procyclical behavior of R&D and that procyclical incentives for innovative activity are also likely to play an important role.

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# 1 Introduction

The Great Recession of 2008-09 led to sharp declines in output and a very slow recovery for most advanced economies. For example, Reifschneider et al. (2015) estimate that the US economy was about 7 percent below its pre-recession trajectory as of late 2014. In the post-recession period, the Congressional Budget Office (CBO) has steadily revised downward its estimate of the potential output path, suggesting that the recession was so severe that it damaged long-run growth prospects for the US economy.

Traditionally, most macroeconomists have analyzed the business cycle independently from the determinants of long-run economic growth. Evidence from the Great Recession (Reifschneider et al. 2015) suggests that there may be important interactions between cyclical fluctuations and the long-run performance of the economy and that the assumed independence of these two branches of research is inappropriate. In response to this evidence, a number of macroeconomists have begun to investigate the channels through which cyclical fluctuations may have a long-run impact. Blanchard et al. (2015) examine several decades of data for a number of advanced economies and find that a significant proportion of recessions are followed by a reduction in the long-run growth rate relative to its pre-recession trend. The authors acknowledge that some of these observations may reflect reverse causality (more pessimistic views about long-run growth could lead to a recession and subsequent slower growth), but even recessions that are identified as plausibly related to demand shocks frequently have long-run effects. This suggests that channels from short-run fluctuations to long-run growth are also likely important.

One area where there may be an interaction between business cycle fluctuations and long-run growth relates to firm-level decisions to devote resources to research and development (R&D). If a severe downturn reduces firms' willingness or ability to engage in R&D activities, this may reduce the likelihood of future innovations and damage long-run growth prospects. If the impact on R&D is significant on an economy-wide level, it likely leads to a reduction in the potential growth path for the entire economy. Along these lines, Comin and Gertler (2006) and Anzoategui et al. (2016) provide a theoretical link between business cycle fluctuations, innovative activity, and long-run growth. Innovators and technology adopters in these models are assumed to have procyclical incentives such that downturns reduce the volume of R&D spending and slow the adoption of existing innovations. Productivity growth in these models is therefore endogenously impacted by cyclical fluctuations and short-run shocks have the potential to impact long-run growth.

In a separate but related literature, there have been a number of studies examining the cyclical behavior of R&D. The vast majority of studies find evidence of procyclical R&D spending (Walde and Woitek 2004; Barlevy 2007; Ouyang 2011; Fabrizio and Tsolmon 2014) and a number of theoretical explanations have been advanced to explain this stylized fact. Aghion et al. (2012) analyze French firm level data and find evidence suggesting credit constraints during recessionary periods play an important role in explaining the cyclical behavior of R&D. Further evidence of a role for credit constraints is provided by Kabukcuoglu (2017) who examines high tech firms during the Great Recession and finds firms without bond ratings had more procyclical R&D. Credit constraints play a vital role in these studies because many of these authors take the view that, consistent with the views of Schumpeter (1939), R&D spending should pick up during a recession when the opportunity cost of innovative activity is low. In other words, absent credit constraints, countercyclical R&D spending is expected.

An alternative explanation is provided by Barlevy (2007) who emphasizes the intertemporal nature of R&D spillovers. In the Barlevy model, innovators weigh near-term profits more highly because profits will become diffused over time, and this generates procyclical innovative activity. Fabrizio and Tsolmon (2014) find that R&D is more procyclical in industries with faster obsolescence and weaker patent protections, providing empirical support for the Barlevy (2007) hypothesis.

This paper builds on the existing literature by extending the cyclical analysis of R&D to the macro level. Most existing studies use firm or industry level data, but in order for this R&D

channel to impact long-run economic growth the fluctuations must be significantly procyclical at the economy-wide level. Likewise, studies that find an important role for credit constraints at the firm level do not necessarily scale to the macroeconomy, especially if large firms (which are presumably less credit constrained) dominate economy-wide R&D.

Our analysis begins with the construction of a theoretical model that is directly motivated by previous work on R&D and credit constraints. The model includes a separate role for output and credit and allows us to investigate their interaction in explaining the cyclicality and symmetry of R&D spending. We empirically investigate the time series properties of and relationships between output, credit, and R&D for a panel of 22 advanced economies. Our analysis reveals strong evidence of procyclical R&D, and contrary to some of the micro level evidence, we find a symmetric response to positive and negative output fluctuations. We find some evidence that credit conditions are particularly important during economic downturns, although this result is primarily driven by the Great Recession. The interaction between the business cycle and credit market conditions in driving R&D fluctuations is consistent with our theoretical model and with some previous micro level studies, but our results suggest non-credit-related explanations are likely to play a role since we find R&D to be procyclical even when credit conditions are accounted for.

The paper proceeds as follows. Section 2 presents the theoretical model, Section 3 describes the data and performs time series specification tests, Section 4 presents the empirical results, and Section 5 provides some concluding comments.

# 2 Model

A number of academic studies report a procyclical pattern for R&D spending at the industry and firm level. Within this literature two leading explanations for the observation of procyclical R&D have emerged. One branch of the literature suggests that the incentives to pursue R&D and adopt new innovations are procyclical (Barlevy 2007; Comin and Gertler 2006; Anzoategui et al.

2016). A second branch of the literature, inspired by Schumpeter (1939), suggests that desired R&D is not procyclical but that credit constraints distort firm behavior (Aghion et al. 2005, 2010, 2012).[1] These studies present evidence that R&D responds to business cycle fluctuations asymmetrically with R&D responding most significantly during recessions. The asymmetry reported by Ouyang (2011) and further explored by Aghion et al. (2012) appears consistent with an important role for credit constraints.

In the theoretical model we take no position on the cyclicality of *desired* R&D, but instead focus on the second branch of the literature and explore the role of credit constraints in explaining the *observed* cyclical behavior of R&D. Our model builds on those in the literature by accounting for both output and credit market conditions.

The model is intended to provide guidance in forming expectations of patterns of R&D spending as business cycle conditions and credit conditions change at the macro level. As is typical in modern macroeconomics, the results are based on a risk neutral representative agent/firm and many potential dynamic aspects are deliberately left out of the model (e.g. higher order autocorrelation in the disturbances to GDP and credit conditions). Although we present a simplified model, the results are consistent with the literature's use of credit constraints to reconcile procyclical and asymmetric R&D at the firm and industry levels with the dominant Schumpterian view (Aghion et al. 2012; Ouyang 2011). Although the theoretical model focuses on the role of credit constraints, in our empirical work we will also consider the possibility of procyclical incentives for R&D as proposed by Barlevy (2007).

Using notation that is standard in the R&D and credit constraint literature, the relationship between productivity adjusted resources devoted to R&D, $n$, and the probability of successfully innovating, $\mu$, is specified as:[2]

[1] Aghion et al. (2010) provide a theoretical model that suggests the long-term share of investment will be procyclical in the face of credit constraints. Aghion et al. (2012) find evidence that in the absence of credit constraints R&D is countercyclical, which is consistent with the opportunity cost theory advanced by Schumpeter (1939).

[2] More specifically, $\mu$ is a Poisson arrival rate. The Poisson specification is memoryless and the probability of innovating is based only on current efforts. For example, the pdf for a Poisson process is $f(x) = \frac{e^{-\mu}\mu^x}{x!}, x = 0, 1, 2, 3, \ldots$

$$n = \frac{R}{\overline{A}} = \frac{\psi\mu^2}{2}.$$

In this equation, $R$ is the firm's level of resources devoted to R&D projects and $\overline{A}$ is a target level of technological advance equivalent to a technological frontier. The equation simply implies that more resources are needed to achieve a higher chance of success, there are diminishing returns to resources devoted to R&D, and a higher target level of technology requires a larger investment.

A successful innovation supplies the firm with a stream of long-run profits, $\pi$. In the following analysis, $\pi$ is taken to be a long-run expected average level of profits associated with a successful research endeavor. Therefore, fluctuations in the expected profit stream are ignored and $\pi$ is assumed to be an exogenous parameter.[3] The R&D funding problem is expressed as a simple optimization problem:

$$\underset{\mu}{Max} \mu\pi - R = \left[\mu\frac{\pi}{\overline{A}} - \frac{\psi\mu^2}{2}\right]\overline{A}.$$

This optimization problem leads directly to an equilibrium probability of innovation, $\mu^* = \frac{\pi}{\overline{A}\psi}$. The firm's optimal R&D spending is $R^* = \frac{\pi^2}{2\overline{A}\psi}$. Allow $X = \delta_x \varpi A$ to represent the firm's retained earnings available to internally fund R&D in the present period, in which $\delta_x$ captures the cyclical nature of output, to be examined in more detail below, and $A$ is the level of technology/productivity. Higher productivity leads to more internal resources available for R&D funding, *ceteris paribus*. $\varpi$ is a constant of proportionality. The amount of credit market financing, CMF, is positive if $R^* > X$:

To be sure, the pdf is $f(x) = e^{-\mu}\mu$ for $x = 1$, whereas the probability of no innovation by date $t$ ($x = 0$) is $f(x) = e^{-\mu}$. Note that the expected value and variance of the Poisson process are both equal to $\mu$; thus, it is an instantaneous probability of a successful research project.

[3]It is straight forward to allow for a shock to $\pi$. It is reasonable to imagine that this shock would be positively correlated with shocks to output. The qualitative results of the model are not impacted by this consideration so long as the shock to the expectation of long-run average profits has a smaller variance than the shock to current output and current retained earnings. This is a very reasonable specification. The simplest model possible is presented.

$$CMF = \left( \frac{\pi^2}{2\overline{A}\psi} - X \right).$$

## 2.1 Credit market financing with a credit constraint

The relationship between productivity adjusted resources devoted to R&D, $\widetilde{n}$, and the probability of successfully innovating, $\widetilde{\mu}$, for the credit constrained firm is

$$\widetilde{n} = \frac{\widetilde{R}}{\overline{A}} = \frac{\psi \widetilde{\mu}^2}{2}.$$

The credit multiplier, $\nu > 1$, is introduced in the specification of resources spent on R&D as follows: $\widetilde{R} = \widetilde{n}\overline{A} = \nu X$. The value of $\nu - 1$ determines the amount of borrowing possible, as a percentage of internal resources, for a firm with retained earnings $X$. Since $X = \delta_x \varpi A$, it is possible to develop an expression of $\widetilde{n}$:

$$\widetilde{n} = \frac{\psi \widetilde{\mu}^2}{2} = \nu \delta_x \varpi \overline{a},$$

where $\overline{a} = \frac{A}{\overline{A}}$ is the firm's proximity to the technological frontier. Solve this expression for $\widetilde{\mu}$ :

$$\widetilde{\mu}^* = \sqrt{\frac{2\nu \delta_x \varpi \overline{a}}{\psi}}.$$

The amount of credit market financing for a constrained firm, $\widetilde{CMF}$, is:

$$\widetilde{CMF} = (\nu - 1)X.$$

The credit constraint binds if $\widetilde{\mu}^* < \mu^*$. Substituting expressions for $\widetilde{\mu}^*$ and $\mu^*$ defines a critical value of the credit multiplier, $\nu^*$, below which credit constraints become binding:

$$v^* = \left(\frac{\pi}{\bar{A}\psi}\right)^2 \frac{\psi}{2\varpi\bar{a}\delta_x}.$$

Note that the value of $v^*$ is determined by the cyclical output parameter, $\delta_x$, but is not dependent on either the credit parameter, $\delta_v$, or the value of the credit multiplier. An output shock lowers a firm's resources for internal R&D funding, $X$, and increases their demand for credit market financing, *ceteris paribus*. Thus, the critical value of the credit multiplier, below which firms become constrained, is raised in light of this increased desire for external funding. It is straightforward to demonstrate that $\widetilde{CMF} < CMF$ if $\tilde{\mu}^* < \mu^*$.

## 2.2 Output and credit shocks

Recall that $\delta_x$ represents output changes due to business cycle fluctuations and their impact on retained earnings and internal firm resources available for R&D. Additionally, allow for changes in credit markets by extending the definition of $\nu$, $\nu = \delta_\nu \bar{\nu}$. $\delta_\nu$ is a parameter, similar to $\delta_x$ for output, which captures the role of credit shocks.

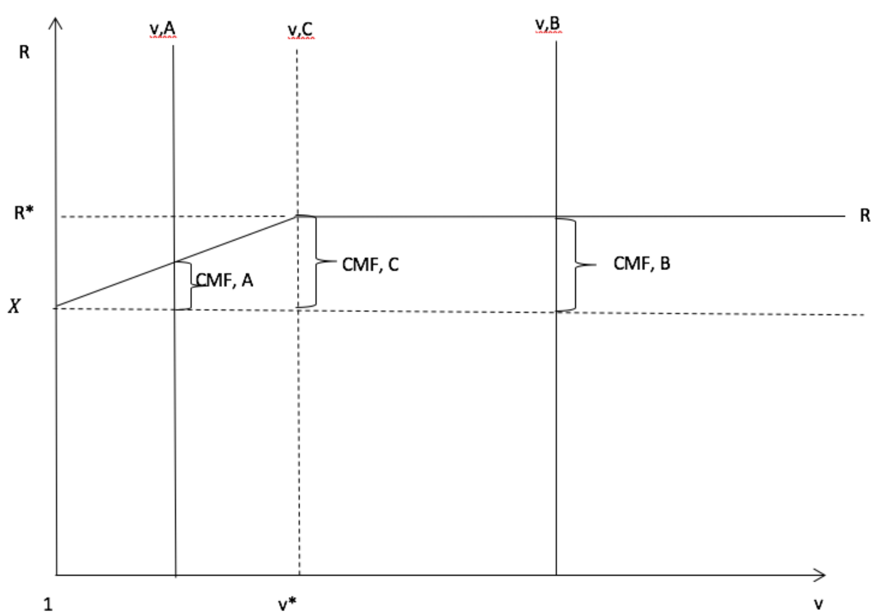



Figure 1: Equilibrium and Credit Constraints

Figure 1 shows equilibrium in the model for three representative firms (A,B,C) with varying levels of access to credit markets. The upper schedule, labeled R, determines the level of R&D spending. The critical value of the credit multiplier, $v^*$, is identified on the horizontal axis. To the left of this value, firms are credit constrained; thus, firm A in the figure is credit constrained, whereas firm B is not. When the firm is credit constrained, relaxing the constraint (i.e. an increase in $v$) increases R&D spending. When the firm is not credit constrained, relaxing the constraint has no impact on the level of R&D spending and the schedule has a slope of zero. The amount of equilibrium credit market funding of R&D, which is found by subtracting $X$ from $R$ is also identified in the graph.

Firms at or near the critical value of the credit multiplier, such as firm C, will be credit constrained whenever the critical value $v^*$ increases. A key to understanding the potential for an asymmetric response of R&D to GDP shocks is understanding that output shocks change the value of $v^*$ independent of a credit shock (a change in $v$ through $\delta_v$).

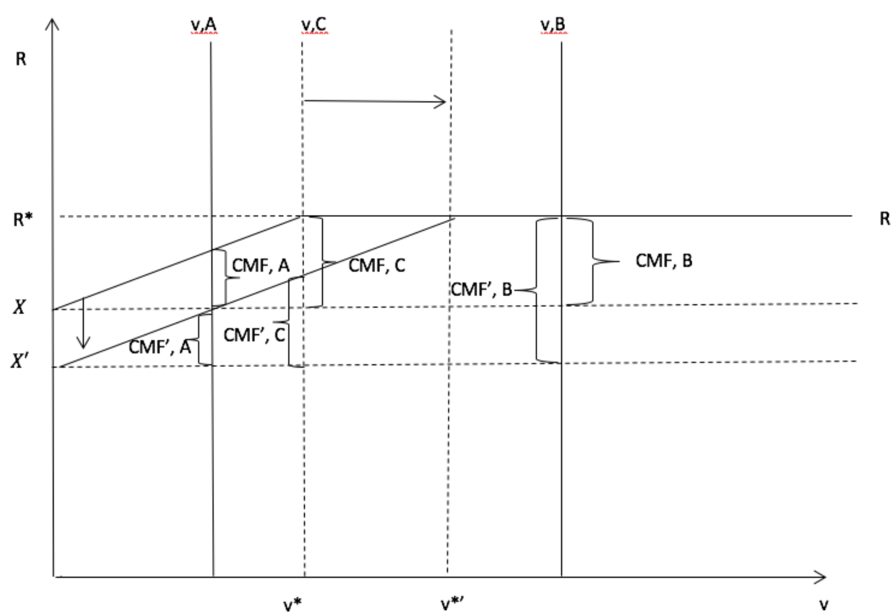


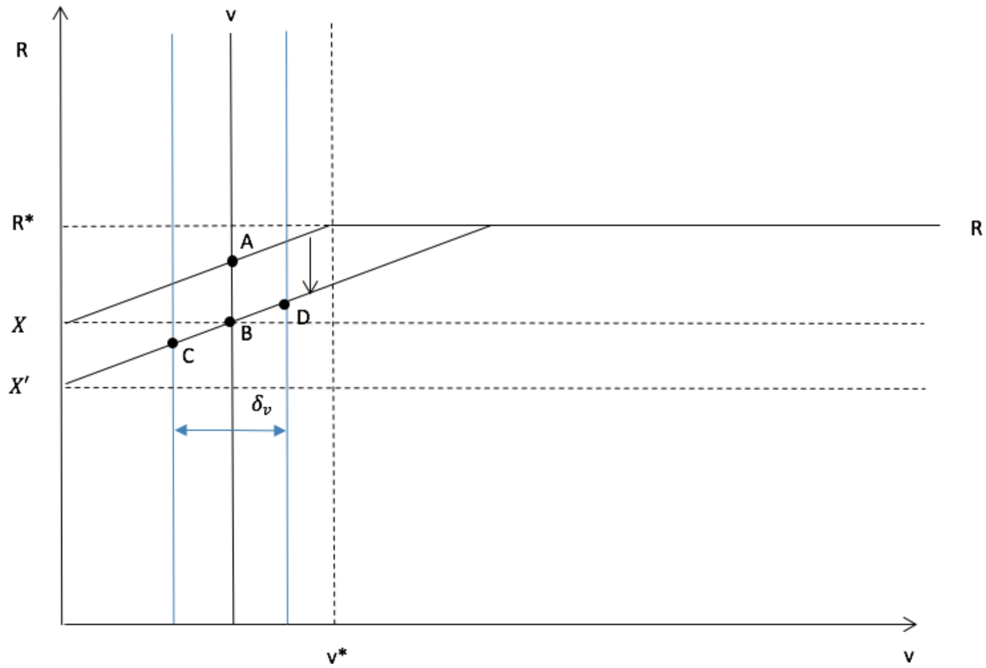

Figure 2: Output Shock

Figure 2 shows that the impact of a negative change in output on R&D spending depends on the degree to which a firm is credit constrained. Recall that we assume in our model that desired R&D spending is constant (or acyclical). First consider firm A, the credit constrained firm. The recession lowers retained earnings and therefore reduces internal resources available for funding R&D. This is depicted by the downward shift in the sloped portion of the R schedule. Given that firm A is credit constrained, it is forced to reduce R&D spending in response to the recession. In the face of an economic expansion, firm A would increase R&D spending thanks to increased retained earnings and a relaxation of the credit constraint. To summarize, the model predicts procyclical R&D spending by credit constrained firms with a symmetrical response to the business cycle.

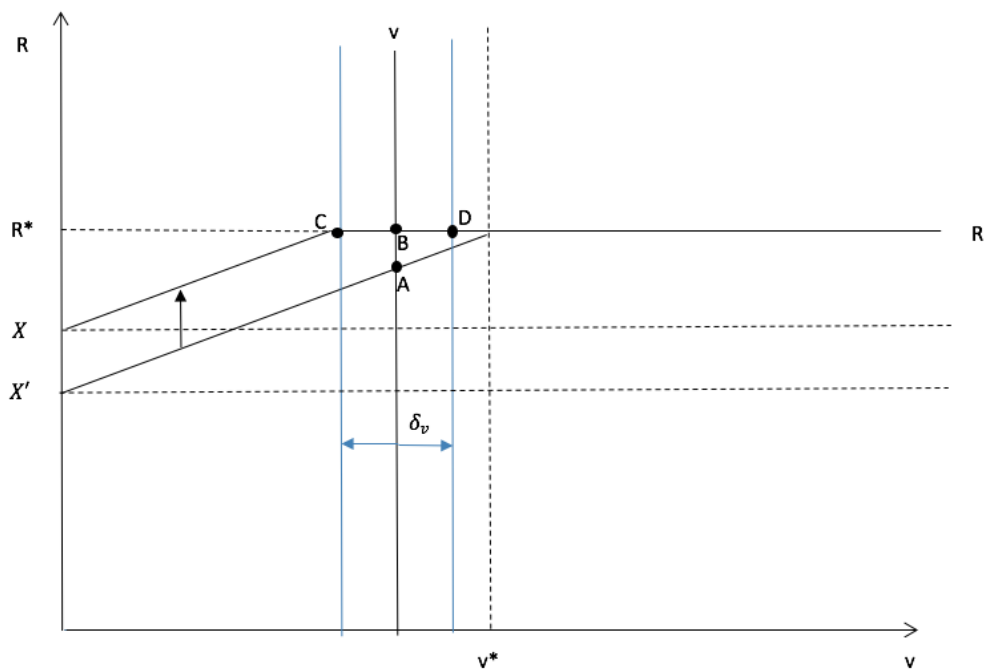
Next, consider the case of a firm that does not face credit constraints, such as firm B. Here, any shortfall of internal financing due to a recession is offset by increased credit market funding of research projects. Likewise, an expansion will not have any impact on R&D, but would simply reduce the required amount of credit market funding. To summarize, the model predicts acyclical R&D spending by non-credit constrained firms.

Finally, consider the case of firm C, which is on the threshold of being credit constrained. Here it is important to recall that a recession increases the critical value of the credit multiplier from $v^*$ to $v^{*}$', increasing the likelihood that firms will face constraints in financing. Firm C was not credit constrained before the recession, but becomes constrained as a result of the recession and the associated increase in $v^*$. In this case, the firm's level of R&D falls. Note that an expansion would have no impact on firm C's R&D spending. To summarize, the model predicts an asymmetric response of R&D to output shocks for firms on the threshold of the credit constraint, in which R&D falls during a recession but remains constant in response to an expansion.

Figure 3 examines the impact of credit market conditions and demonstrates a potentially important interaction with the business cycle. We once again hold the desired level of R&D constant and focus on the case of firms near the credit constraint threshold. In Panel (a) of Figure 3, the firm is assumed to be moderately credit constrained at point A.




(a) Negative Output Shock




(b) Positive Output Shock

Figure 3: Credit Shock Interaction with Output Shock

Now consider the impact of a combination of output and credit changes. A recession moves the firm from A to B, reducing R&D spending. Add a reduction in credit ($\delta_v < 0$) and R&D falls further to point C, while improving credit conditions ($\delta_v > 0$) mitigates the impact of the recession somewhat by increasing R&D to point D. Panel (b) of Figure 3 shows the impact of credit in combination with an expansion, again for a firm with a credit multiplier lower than but very close to $v^*$. In this case, an expansion makes the credit change irrelevant. The economic expansion causes R&D to increase from A to B, while the change in credit causes a move to point C ($\delta_v < 0$) or point D ($\delta_v > 0$) with no impact on R&D.

To summarize, Figure 3 demonstrates that the impact of a deterioration in credit market conditions depends on the cyclical state of the economy. For firms on the threshold of the credit constraint, the model predicts that a reduction in credit will have a significant (and symmetrical) impact on R&D during economic downturns (Panel (a)), but credit conditions will have no impact on R&D during economic expansions (Panel (b)). The model motivates our exploration of interactions between business cycle fluctuations and credit in the empirical work that follows.

# 3 Data

The data used for this paper are combined from three sources. First, the OECD provides data on business enterprise R&D spending from 1982-2011, which dictates the time period used in this study.[4] The OECD reports significant gaps in R&D spending for some countries, resulting in an unbalanced panel. Next, GDP data from 1982-2011 is available from the IMF.[5] Finally, credit data is retrieved from an extensive new international database created by the Bank for International Settlements (BIS).[6] The financial cycle literature has typically used growth in real total non-financial private sector credit along with a proxy for housing prices (Borio et al. 2014). The new BIS data

[4]http://stats.oecd.org/Index.aspx?DataSetCode=GERD_FUNDS
[5]http://www.imf.org/external/ns/cs.aspx?id=28
[6]http://www.bis.org/statistics/credtopriv.htm. See Dembiermont et al. (2013) for details.

set splits the credit data into household and corporate sectors. Since this paper focuses on credit available to corporations engaging in R&D rather than credit extended to households (e.g. mortgages), the series on credit to the non-financial corporate sector from 1982-2011 is used. All data are transformed into real terms, denominated in local currency, and measured in logs.

The final data set consists of 457 observations on 22 countries. Although the IMF classifies more than 22 countries as advanced economies, the availability of data on R&D spending from the OECD limits the sample to these countries. Summary statistics for the log first differenced value of these variables and a list of countries included in the final data set are provided in Table 1.

Table 1: Summary Statistics

| | $dRD_{i,t}$ | | | $dGDP_{i,t}$ | | | $dCR_{i,t}$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | (Std. Dev.) | N | Mean | (Std. Dev.) | N | Mean | (Std. Dev.) |
| All 22 Countries | 457 | 0.051 | (0.085) | 457 | 0.026 | (0.026) | 395 | 0.041 | (0.055) |
| Australia | 26 | 0.091 | (0.088) | 26 | 0.033 | (0.014) | 26 | 0.048 | (0.065) |
| Austria | 2 | 0.052 | (0.016) | 2 | 0.029 | (0.010) | 1 | 0.062 | (0.000) |
| Belgium | 26 | 0.027 | (0.048) | 26 | 0.019 | (0.016) | 26 | 0.053 | (0.048) |
| Canada | 30 | 0.039 | (0.074) | 30 | 0.025 | (0.022) | 30 | 0.032 | (0.038) |
| Czech Republic | 16 | 0.055 | (0.109) | 16 | 0.028 | (0.029) | 15 | 0.006 | (0.066) |
| Denmark | 20 | 0.079 | (0.053) | 20 | 0.016 | (0.023) | 8 | 0.012 | (0.029) |
| Finland | 14 | 0.054 | (0.068) | 14 | 0.024 | (0.036) | 14 | 0.045 | (0.035) |
| France | 29 | 0.033 | (0.034) | 29 | 0.018 | (0.015) | 29 | 0.038 | (0.032) |
| Germany | 30 | 0.026 | (0.043) | 30 | 0.018 | (0.021) | 16 | 0.023 | (0.037) |
| Greece | 3 | -0.042 | (0.170) | 3 | 0.032 | (0.008) | 0 | | |
| Ireland | 30 | 0.081 | (0.068) | 30 | 0.041 | (0.040) | 9 | 0.106 | (0.080) |
| Italy | 29 | 0.025 | (0.069) | 29 | 0.015 | (0.019) | 29 | 0.032 | (0.040) |
| Japan | 29 | 0.041 | (0.057) | 29 | 0.021 | (0.026) | 29 | 0.024 | (0.050) |
| Korea | 15 | 0.075 | (0.075) | 15 | 0.044 | (0.038) | 15 | 0.055 | (0.066) |
| Luxembourg | 2 | -0.284 | (0.428) | 2 | 0.022 | (0.009) | 2 | -0.077 | (0.016) |
| Netherlands | 18 | 0.033 | (0.064) | 18 | 0.028 | (0.014) | 8 | 0.042 | (0.028) |
| Norway | 9 | 0.076 | (0.086) | 9 | 0.021 | (0.025) | 9 | 0.065 | (0.058) |
| Portugal | 28 | 0.101 | (0.132) | 28 | 0.024 | (0.025) | 28 | 0.032 | (0.060) |
| Singapore | 16 | 0.091 | (0.150) | 16 | 0.056 | (0.043) | 16 | 0.050 | (0.085) |
| Spain | 29 | 0.067 | (0.086) | 29 | 0.027 | (0.021) | 29 | 0.050 | (0.058) |
| United Kingdom | 26 | 0.017 | (0.049) | 26 | 0.026 | (0.023) | 26 | 0.059 | (0.065) |
| United States | 30 | 0.039 | (0.046) | 30 | 0.027 | (0.020) | 30 | 0.042 | (0.039) |

Note: $dGDP_{i,t}$ is the log first differenced value of country $i$'s GDP in year $t$. $dCR_{i,t}$ is the log first differenced value of credit extended to non-financial corporate sector in country $i$ in year $t$. $dRD_{i,t}$ is the log first differenced value of business enterprise R&D spending in country $i$ in year $t$.

The full panel of 22 countries is unbalanced with gaps in R&D data for many economies. For panel time series specification tests, which require a balanced panel, we restrict attention to economies with complete R&D data: Canada, France, Italy, Japan, Spain, and the United States. However, we utilize the full panel of 22 economies for our empirical analysis.

Since the data are annual time series, unit roots and non-stationarity are a concern. Table 2 shows the results of panel unit root tests. The first row is the Livin-Lin-Chu (LLC) test, whereas the second row, labeled DF, is an augmented Dickey-Fuller (DF) test. Each of these tests require a balanced panel and are appropriate for our data in the sense that the number of cross sectional panels (N) are considered to be constant as T tends to infinity (DF) or the ratio N/T tends to zero as T grows faster than N (LLC). The most significant difference in these tests is the specification of the autoregressive parameter, which is assumed to be equal across panels with the LLC test but is allowed to vary by cross section with the DF test. The unit root tests of the levels of the variables include a time trend. All tests allow for panel specific intercepts, optimal autoregressive lags are chosen based on the AIC criteria, and up to three lags are allowed. In every case, the optimal lag is less than three.

Table 2: Panel Unit Root Tests

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | RD | GDP | CR | dRD | dGDP | dCR |
| LLC | -1.097 | 0.061 | -2.131** | -6.927*** | -4.958*** | -3.563*** |
| DF | 0.803 | 1.243 | -0.216 | -3.651*** | -2.755*** | -3.321*** |

Note: LLC is the Livin-Lin-Chu panel unit root test, whereas DF is an augmented Dickey-Fuller panel unit root test. Optimal lags based on AIC and the tests of levels include constant and trend terms. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

The LLC tests the null hypothesis that all panels are nonstationary against the alternative that they are stationary. The results in columns (1) - (3) in Table 2 suggest that the panels contain unit roots, with the exception of credit. At the 5% significance level the null hypothesis that all panels are nonstationary. The DF tests the null hypothesis that all panels contain a unit root against the alternative that at least one is stationary. This test indicates unit roots across the levels of all three variables.

To test the order of integration for the variables, we test for unit roots in the 1st differences of the levels. These results are reported in columns (4) - (6) in Table 2. No evidence of non-stationarity is found in any of the panel unit root tests of the log 1st differences, suggesting that the variables are integrated of order one, I(1).

Before concluding that a model in 1st differences is appropriate, the issue of cointegration must be considered. If a cointegrating vector exists between RD, GDP, and CR, an appropriate model must specify the dynamics correctly by including an error correction mechanism. In the absence of cointegration, a model in first differences is appropriate.

Table 3: Panel Cointegration Tests

| | Test Statistic | Robust P-value |
|---|---|---|
| Ga | 3.134 | 0.952 |
| Gt | -0.289 | 0.490 |
| Pt | 0.622 | 0.646 |
| Pa | 2.452 | 0.938 |

Note: The Westerlund cointegration tests, which allow for a constant and trend in the cointegrating relationship, are z scores that can be compared to the standard normal distribution. Robust p-values are based on bootstrapped critical values and are robust to cross-sectional dependence. The null hypothesis of no cointegration is rejected if z score is below the critical value.

Table 3 provide four tests of panel cointegration based on Westerlund (2007). The test is based on the following specification:

$$dRD_{i,t} = \alpha_i(\delta_t' a_t + RD_{i,t-1} - \beta_i' x_{i,t-1}) + \sum_{j=1}^{p_i} \left(\alpha_{i,j} dRD_{i,t-j}\right) + \sum_{j=1}^{p_i} \left(\gamma_{i,j} dx_{i,t-j}\right) + e_{i,t},$$

where $d$ is a first difference operator, $a = \begin{bmatrix} 1 \\ t \end{bmatrix}$, and $x_{i,t} = \begin{bmatrix} GDP_{i,t} \\ CR_{i,t} \end{bmatrix}$. This test of panel cointegration requires a balanced panel. The deterministic components, $a$, allow for a stochastic trend. The second term is the error correction mechanism, where $\alpha_i$ is panel $i$'s speed of adjustment parameter. The lag length, $p_{i,}$ for each time series is chosen based on the best AIC. If the levels of RD, GDP and CR are cointegrated, it is expected that $\alpha_i < 0$. The test for panel cointegration is a test of the null hypothesis that $\alpha_i = 0$ for all $i$. The first two tests are group means tests for cointegration, in which the appropriate alternative hypothesis is $\alpha_i < 0$ for at least one $i$. The second two tests restrict the $\alpha_i$ to be equal across panels such that the appropriate alternative is $\alpha_i = \alpha < 0$ for all $i$. The robust p values reported in Table 3 are bootstrapped and account for the possibility that there is cross sectional interdependence in the error terms, $e_{i,t}$. In every case we fail to reject the null hypothesis of no cointegration. The conclusion is that a model in first differences, without an error correction specification, is adequate for investigating the relationship between R&D, GDP, and credit, henceforth denoted as dRD, dGDP, and dCR, respectively.

# 4 Empirical analysis

Having settled on the appropriate transformation of the variables, we now explore the relationship between R&D, output, and credit, using three panel econometric techniques: fixed effects, random effects, and Arellano-Bond dynamic panel estimation. The goal of our empirical analysis is to evaluate the cyclicality and symmetry of R&D for a sample of advanced economies. Our empirical work is motivated by the theoretical model presented in Section 2. Table 4 summarizes the predictions of the theoretical model with varying degrees of credit constraints. The final two columns of Table 4 consider the possibility of a cyclical pattern in desired R&D à la Schumpeter (1939) or Barlevy (2007).

Table 4: Theoretical Predictions of R&D Cyclicality

| Cyclicality of Desired R&D | Acyclical | Acyclical | Acyclical | Countercyclical (Schumpeter) | Procyclical (Barlevy) |
|---|---|---|---|---|---|
| Credit Constraint Assumption | Fully credit constrained | Threshold credit constrained | None | None | None |
| Predicted R&D Cyclicality | Symmetric, Procyclical R&D | Asymmetric R&D | Acyclical R&D | Countercyclical R&D | Symmetric, Procyclical R&D |

We first investigate the potential asymmetry of R&D to output and credit conditions by estimating the following fixed effects and random effects panel data regression specifications:

$$dRD_{i,t} = x_{i,t}^{'} B + v_i + e_{i,t},$$

where $v_i$ is the country fixed effects or random effects.

Table 5: Specification Tests

| | (1) Wooldridge | (2) Hausman |
|---|---|---|
| Test Stastistic | 2.207 | 29.59*** |
| P-Value | 0.155 | 0.000 |

Note: This table reports the specification tests to compare the fixed effects and random effects specifications. * indicates significance at 10% level, ** indicates significance at 5% level, and *** indicates significance at 1% level.

Fixed and random effects specifications with additional lags of the explanatory variables are investigated, but the estimates are generally found to be insignificant. For the fixed effects specification, it is possible to calculate information criteria for choosing a properly specified model. The AIC and BIC criteria are both minimized in a specification without additional lags. Additional specification tests associated with these models are reported in Table 5. Column (1) of Table 5 presents the Wooldridge (2002) test for serial correlation in the errors of the panel data model. The null hypothesis of no serial correlation cannot be rejected. In column (2), we present results from a Hausman test, where the null hypothesis states that the coefficients of a fixed and random effects estimator are equal. In our case, we reject the null hypothesis, suggesting that the fixed effects model is appropriate.

Table 6 presents results for several fixed effects regression specifications, where the country level fixed effect absorbs unobserved country level characteristics. In each case we seek to explore how R&D responds to business cycle fluctuations and credit conditions. The simplest specification in column (1) provides evidence that R&D is strongly procyclical at the macro level for our sample of advanced economies. The specification in column (2) tests for the possibility of asymmetry in the cyclical behavior of R&D. Recall that Ouyang (2011) and Aghion et al. (2012) provide evidence of an asymmetric relationship at the sectoral and firm levels respectively. In our macro level analysis, we find that the coefficients on positive and negative output growth are approximately equal (and a Wald test overwhelmingly fails to reject equality), suggesting a symmetrical relationship between output growth and R&D. Recall from Table 4 that symmetric procyclical R&D is theoretically consistent with a model where firms are credit constrained. We therefore add a control for credit conditions in column (3), which restricts the sample somewhat, and find that R&D exhibits positive co-movement with credit flows lending some credibility to theories emphasizing a role for credit constraints. However, it is also important to note that we continue to find symmetrically procyclical R&D even after controlling for aggregate credit flows.

Because our credit variable reflects the equilibrium flow of credit, the specification in column (3) does not identify whether the positive association between credit flows and R&D is driven by demand or supply side innovations in credit markets. In an attempt to shed further light on the role of credit we replace the credit flows measure with a country specific real interest rate in column (4).[7] The positive and statistically significant coefficient on the real interest rate runs counter to the prediction of adverse credit supply shocks reducing R&D spending. On the demand side of credit markets a higher real interest rate is a proxy for firms' increased desire for expanded credit to fund all sorts of projects that include, but certainly are not limited to R&D.[8]

As a final attempt to disentangle the influence of credit supply and demand factors on R&D, we create an interaction term between the demeaned values of both credit flows and real interest rates. We then classify the interaction term as reflecting credit demand factors for observations with positive values (i.e. above country average) for both credit flows and real interest rates. Credit supply innovations are identified as observations where demeaned credit flows and real interest

[7] The real interest rate is the lending rate adjusted for inflation taken from IMF's International Financial Statistics.

[8] We maintain that R&D spending is a relatively small fraction of overall credit financing and that credit flows and real interest rates can be assumed exogenous to the R&D decision.

rates have opposite signs. The regression reported in column (5) includes all four possibilities for credit market conditions with the innovations normalized to have positive signs for ease of coefficient interpretation. We find a positive and highly significant coefficient on our positive credit demand variable which suggests that demand side forces in credit markets are responsible for the observed positive relationship between higher real interest rates, higher credit flows, and increased desired R&D spending. Our finding that R&D is symmetrically procyclical and that increases in R&D spending are associated with credit demand is consistent with models that emphasize procyclical fluctuations in desired R&D such as Barlevy (2007) and Comin and Gertler (2006).

In the final two columns of Table 6 we include an interaction term between credit conditions and GDP growth to test for the possibility that credit constraints are most important during economic downturns as suggested by Aghion et al. (2012) and modeled in Figure 3. The interaction term could be motivated by a convex relationship between GDP growth and credit conditions, where output and credit are largely unrelated for small fluctuations, but highly correlated for large shocks. The specification presented in column (6) provides further evidence that R&D is symmetrically procyclical, but it also includes a highly significant interaction between credit growth and economic contractions. The interaction term provides macroeconomic evidence that is consistent with the Aghion et al. (2012) firm level finding that credit conditions are more likely to impact R&D during economic downturns. It is important to note however that our results suggest R&D is procyclical even after controlling for credit, which is contrary to the Aghion et al. (2012) finding of countercyclical firm level R&D in the absence of credit constraints. Furthermore, our finding of a significant interaction between credit and economic downturns appears to be driven primarily by the Great Recession. In column (7) we limit the sample to observations before 2007 and we fail to find a significant interaction effect, but our primary finding of symmetrical procyclical R&D is robust to the exclusion of the Great Recession.[9]

[9] As an additional robustness check, we ran all of the specifications in Table 6 excluding the countries with limited observations (Austria, Greece, Luxembourg, and Norway) and the results are qualitatively similar.

Table 6: Fixed Effects Estimation Results
(Dependent Variable: *dRD*)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *GDPgrowth* | 0.995*** | | | | | | |
| | (0.146) | | | | | | |
| *posGDP* | | 0.825*** | 1.097*** | 0.796*** | 1.439*** | 1.213*** | 1.251*** |
| | | (0.320) | (0.378) | (0.298) | (0.358) | (0.374) | (0.401) |
| *negGDP* | | 1.100*** | 1.047*** | 1.441*** | 1.319*** | 0.913*** | 0.851** |
| | | (0.228) | (0.232) | (0.250) | (0.258) | (0.232) | (0.379) |
| *Credit* | | | 0.358*** | | | | |
| | | | (0.073) | | | | |
| *RealInterestRate* | | | | 0.368*** | | | |
| | | | | (0.140) | | | |
| *posCreditDemand* | | | | | 14.584*** | | |
| | | | | | (5.577) | | |
| *negCreditDemand* | | | | | -6.738 | | |
| | | | | | (4.572) | | |
| *posCreditSupply* | | | | | 5.451 | | |
| | | | | | (9.022) | | |
| *negCreditSupply* | | | | | -4.913 | | |
| | | | | | (5.997) | | |
| *posCredit* | | | | | | 0.133 | 0.411** |
| | | | | | | (0.184) | (0.201) |
| *negCredit* | | | | | | 0.071 | -0.020 |
| | | | | | | (0.166) | (0.190) |
| $posGDP \times Credit$ | | | | | | 9.223 | 1.092 |
| | | | | | | (6.794) | (7.334) |
| $negGDP \times Credit$ | | | | | | -18.423*** | -2.450 |
| | | | | | | (4.834) | (10.372) |
| Sample | All obs. | All obs. | All obs. | All obs. | All obs. | All obs. | Pre-2007 |
| $R^2$ | 0.10 | 0.10 | 0.17 | 0.15 | 0.21 | 0.20 | 0.14 |
| $N$ | 457 | 457 | 395 | 401 | 340 | 395 | 314 |

Note: This table reports the results for the fixed effects specifications. Robust standard errors are presented in parentheses. Country fixed effects are suppressed. * indicates significance at 10% level, ** indicates significance at 5% level, and *** indicates significance at 1% level.

As a robustness check for our baseline fixed effects regressions we report, in Table 7, results for dynamic panel regressions. Although the Arellano-Bond dynamic panel estimators are derived for a relatively large N and small T which is not particularly descriptive of our dataset, the results are qualitatively similar to the fixed effects estimates reported in Table 6. Once again, we find robust evidence suggesting R&D is symmetrically procyclical even after controlling for credit market conditions.

Table 7: Arellano-Bond Dynamic Panel Estimation Results
(Dependent Variable: *dRD*)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| *L.dln_realRD_LC* | 0.239*** | 0.240*** | 0.160** | 0.191*** | 0.111** | 0.174*** | 0.128** |
| | (0.063) | (0.064) | (0.065) | (0.059) | (0.050) | (0.062) | (0.057) |
| *GDPgrowth* | 1.051*** | | | | | | |
| | (0.240) | | | | | | |
| *posGDP* | | 0.936*** | 1.203*** | 0.903** | 1.441*** | 1.316*** | 1.263*** |
| | | (0.311) | (0.257) | (0.426) | (0.418) | (0.300) | (0.461) |
| *negGDP* | | 1.110*** | 1.064*** | 1.547*** | 1.432*** | 0.890*** | 0.941 |
| | | (0.262) | (0.289) | (0.171) | (0.184) | (0.206) | (0.663) |
| *Credit* | | | 0.324*** | | | | |
| | | | (0.089) | | | | |
| *RealInterestRate* | | | | 0.347 | | | |
| | | | | (0.237) | | | |
| *posCreditDemand* | | | | | 14.832** | | |
| | | | | | (7.300) | | |
| *negCreditDemand* | | | | | -6.891 | | |
| | | | | | (5.218) | | |
| *posCreditSupply* | | | | | 12.751 | | |
| | | | | | (12.741) | | |
| *negCreditSupply* | | | | | -0.941 | | |
| | | | | | (7.926) | | |
| *posCredit* | | | | | | 0.222 | 0.502** |
| | | | | | | (0.260) | (0.196) |
| *negCredit* | | | | | | -0.035 | -0.080 |
| | | | | | | (0.164) | (0.183) |
| *posGDP* $\times$ *Credit* | | | | | | 2.772 | -2.880 |
| | | | | | | (6.200) | (7.076) |
| *negGDP* $\times$ *Credit* | | | | | | -18.358*** | -1.050 |
| | | | | | | (5.862) | (9.661) |
| Sample | All obs. | All obs. | All obs. | All obs. | All obs. | All obs. | Pre-2007 |
| *N* | 404 | 404 | 352 | 354 | 302 | 352 | 277 |

Note: This table reports the results for the Arellano-Bond dynamic panel specifications. Regressors in the Arellano-Bond specifications are predetermined and up to 3 lags are used as instruments. Robust standard errors are presented in parentheses. Country fixed effects are suppressed. * indicates significance at 10% level, ** indicates significance at 5% level, and *** indicates significance at 1% level.

In order to quantify the economic significance of our results, consider some back of the envelope calculations for the US during the Great Recession. The value of *negGDP* for the US in 2009 is -0.056 (indicating GDP growth was 5.6% below average), while *Credit* takes on a value of -0.046 (indicating credit growth was 4.6% below average). Plugging these values into our fixed effects specification suggests that the R&D growth rate is predicted to fall by 9.7 percentage points – with approximately half of the effect coming from the negative output shock and half from the interaction between the output and credit shocks. The model's prediction for US R&D growth during the Great Recession is approximately correct as actual growth in US R&D was -5.4% in 2009, which is 9.3 percentage points below its sample mean.

Our primary finding of symmetrically procyclical R&D is remarkably robust across all the specifications presented in Tables 6 and 7. Our results also suggest that R&D is procyclical even after controlling for credit conditions, contrary to Aghion et al. (2012) who find countercyclical R&D in the absence of credit constraints. One interpretation of our results, therefore, is that credit market fluctuations are not sufficient to fully explain the procyclical behavior of R&D at the macro level. This leaves open the possibility that a significant fraction of cyclical fluctuations in R&D reflect changes in desired R&D and suggests that models such as Barlevy (2007) and Comin and Gertler (2006) are appropriate in their assumption of procyclical incentives for innovative activity. In order to fully explain the procyclical pattern of R&D in a way that is consistent with the dynamics of long run growth and convergence, it seems likely that one must incorporate both credit market frictions and a mechanism for cyclical fluctuations in desired R&D. In fact, the back of the envelope calculations from our model above suggest that half of the fall in US R&D spending during the Great Recession is associated with credit market conditions, while the other half is more directly related to the recession.

# 5 Conclusion

We find robust evidence of procyclical R&D spending at the macro level in a panel of 22 advanced economies. Contrary to some of the micro level evidence, we find a symmetric response of R&D to positive and negative real GDP fluctuations. We also find a significant co-movement of R&D with credit flows but conclude that this relationship is more likely driven by credit demand rather than credit supply constraints. We do find some evidence for an interaction between cyclical and credit conditions which suggests credit conditions are particularly important during economic downturns, although this result is driven primarily by the Great Recession. Most importantly, our remarkably robust finding that R&D is significantly procyclical even after controlling for credit market conditions can be interpreted as evidence that a significant fraction of fluctuations in observed R&D likely reflects changes in desired R&D rather than credit constraints.

This study helps close a gap between micro studies of R&D and the recently developing literature examining links between cyclical fluctuations and long-run economic growth. Our finding that R&D is significantly procyclical at the macro level for advanced economies suggests one channel through which business cycle fluctuations may impact long-run growth. For example, our regression estimates suggest that the combination of negative output and credit shocks during the Great Recession reduced R&D spending by approximately 10% in the US relative to its pre-recession trend. This economically significant R&D gap has almost certainly damaged long-run growth prospects for the US economy.

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