

Macroeconomic Shocks and Corporate R&D

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Abstract

This paper investigates the impact of output and credit market shocks on R&D spending in advanced economies and builds on the commonly accepted view that credit constraints lead to procyclical R&D spending. A theoretical model is developed where output and credit shocks are treated separately, though these shocks may be highly correlated. The estimation procedure utilizes a panel vector autoregression (VAR) in order to empirically identify the role of credit market shocks separately from the output shocks more commonly studied in the existing literature. The primary empirical findings can be summarized as follows: (1) R&D responds pro-cyclically to output shocks at the macroeconomic level, and (2) R&D co-moves positively with credit. More concretely, the results indicate that negative output shocks induce a simultaneous and subsequent contraction in credit and R&D consistent with a model where credit constraints drive cyclical adjustments to R&D. The impact of output and credit shocks on R&D are economically significant and a simulation exercise suggests the shocks associated with the global financial crisis have reduced US R&D by 10% relative to the pre-crisis path.

JEL classification codes: C32, E32, E44

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1 Introduction

In the aftermath of the global financial crisis, economists and policymakers are concerned not only with the slow pace of recovery but also with the possibility that the severity of the recession has damaged long-run growth prospects. For example, the severe recession may have impacted the willingness and ability of firms to engage in R&D, which in turn would reduce the likelihood of future innovation and damage growth prospects. If R&D was significantly impacted on an economy-wide level, it would likely lead to a reduction in the potential long-run growth path for the entire economy.

Theoretical discussions of the relationship between R&D and the business cycle date back at least as far as Schumpeter (1939), who argued that innovative activity is likely concentrated in downturns when the opportunity cost in terms of forgone output and profits is low. This opportunity cost theory suggests a countercyclical pattern of R&D spending (R&D should rise during recessions and fall during expansions), but economists generally find the opposite result. Explanations for the common finding of procyclical R&D have generally focused on a role for credit conditions which make it more likely that firms will engage in R&D during expansions rather than during recessions when firms might be credit constrained.¹

The existing literature on R&D and credit constraints can be parsed along several dimensions including (1) the empirical methodology (panel data analysis versus single equation time series models), (2) the level of aggregation in the data (firm, industry, or macro level analysis), and (3) the treatment of credit conditions (ranging from financial development proxies to firm-level credit measures). The review here focuses on several recent and prominent contributions that are most closely related to this paper.

Saint-Paul (1993), Walde and Woitek (2004) and Ouyang (2011) each establish the general

¹Barlevy (2007) provides an alternative explanation. He suggests that innovators weight near-term profits highly because profits will become diffused by competitors over time. The implication is that innovative activity (R&D) will be procyclical because expected short term profits are higher during boom times.

result of procyclical R&D using time series analysis. Saint-Paul (1993) analyzes macro level productivity, R&D, and the business cycle using a semi-structural VAR for OECD economies and finds some evidence in support of the view that business cycles have significant effects on R&D/productivity. Walde and Woitek (2004) use OECD countries as the unit of analysis and look at annual data from 1973-2000. Correlations are calculated after filtering the log per capita data with a number of different methodologies (including HP filter, simple difference, etc). Generally positive contemporaneous correlations with varying degrees of statistical significance are reported. The only significant exception is Italy, where R&D appears to be countercyclical. On the other hand, Ouyang (2011) analyzes industry level data for 20 US manufacturing industries over the 1958-1998 time period. He finds evidence supporting Walde and Woitek (2004), but reports that reductions in R&D during recessions is the primary force behind procyclical R&D.

Aghion, Angeletos, Banerjee, and Manova (2010) (hereafter, AABM) provide a macro level study of the role of credit constraints on the composition of investment in OECD countries. Although they do not explicitly focus on R&D, their theoretical model suggests that the long-term share of investment will be procyclical in the face of credit constraints. Empirically, AABM (2010) find that the impact of commodity price shocks on long-term investment is mitigated by financial development (or exacerbated by financial constraints). They interpret this result as evidence that credit constraints are associated with more procyclical long term investment.

Aghion, Askenazy, Berman, Cetto, and Eymard (2012) (hereafter, AABCE) extend the analysis of the previous literature to address the cyclicity of R&D using data at the firm level in France from 1994-2004. Using firm level data on "payment incidents" to construct a proxy for credit constraints, they demonstrate that current bank credit is significantly impacted by previous payment incidents and that credit impacts firms' ability to fund R&D. The cyclicity of R&D is demonstrated in relation to firm level sales. R&D appears to be countercyclical for firms that are not credit constrained, but it is procyclical for firms that are credit constrained (i.e. have had past payment incidents). It is unclear if these firm level results imply overall countercyclical or pro-

cyclical R&D at the macro level. The authors note that their findings do not necessarily translate to the macroeconomy, especially if the bulk of R&D is concentrated in a small number of large (less credit constrained) firms. They explore the aggregate implications by presenting results weighted by firm size. The similarity between weighted and unweighted results suggests procyclical R&D at the macro level. However, the authors close the paper by suggesting that further work on the role of credit constraints at the macro level is needed.

Finally, Campello, Graham, and Harvey (2010) survey 1,050 CFOs about credit constraints and planned investment during the global financial crisis of 2008. A majority of surveyed firms self-report as being credit constrained during the crisis and most constrained firms report that attractive investment opportunities were curtailed by the credit crisis.

This paper makes a number of significant contributions to the existing literature. First, it focuses on the cyclical behavior of R&D at the macro level, while most existing studies use firm or industry level data. The firm/industry evidence suggests that the finding of procyclical R&D is likely related to credit conditions, but this result has not been confirmed on a macroeconomic level. Second, this paper jointly models the time series behavior of output, credit, and R&D, while most previous studies have either calculated simple correlations or attempted to identify output shocks while treating credit conditions as exogenous.

This paper extends the existing literature by providing a simple model of R&D investment that is directly motivated by previous work on R&D and credit constraints. The theoretical model incorporates both output and credit market shocks and motivates the empirical analysis. The empirical investigation employs a panel vector autoregression (VAR), which not only models the time series properties of output, credit, and R&D for 19 advanced economies but also identifies the endogenous response of credit and R&D to macroeconomic shocks. The key findings suggest that shocks to output and credit are significant drivers of R&D and the identified impulse response functions are consistent with credit constraints as an explanation for procyclical R&D at the macro level in advanced economies.

The paper is organized as follows: Section 2 presents the model, Section 3 describes the data, Section 4 presents the empirical results, and Section 5 provides some concluding comments.

2 Model

The level of financial development is a key determinant of R&D funding, productivity growth, and volatility/stability (Levine and Zervos (1989); Levine, Loayza, and Beck, (2000); Beck, Demirguc-Kunt, Laeven, and Levine (2008)). The following model of R&D spending and credit constraints is directly motivated by Aghion and Saint-Paul (1998) and Aghion, Banerjee, and Piketty (1999) and includes separate shocks for output and credit markets. The model is intended to provide an exposition of a firm's R&D decisions and the role of credit constraints in these decisions. Therefore, the model abstracts from the determination of GDP and long run productivity trends, treating these aspects of the model as exogenous and outside of the control of the firm.

2.1 Credit market financing without credit constraints

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, μ , is specified as

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

In this equation R is the firm's level of resources devoted to R&D projects and \hat{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 discounted stream of profits from the R&D

project, π . In the following analysis, π is taken to be profits associated with a successful research endeavor and depends, in part, on current macroeconomic conditions. The R&D funding problem is expressed as a simple optimization problem:

$$\max_{\mu}(\mu\pi - R) = \left[\mu \frac{\pi}{\hat{A}} - \frac{\psi\mu^2}{2} \right] \hat{A}.$$

This optimization problem leads directly to an equilibrium probability of innovation, $\mu^* = \frac{\pi}{\hat{A}\psi}$. The firm's optimal and desired R&D spending is $R^* = \frac{\pi^2}{2\hat{A}\psi}$.

Next the firm's R&D decisions are linked to exogenous macroeconomic conditions. Define X as a firm's retained earnings, higher retained earnings give the firm more resources for use in conducting research. Retained earnings are a function of macroeconomic conditions. Define the GDP gap as \tilde{Y} and allow retained earnings to be a function of the GDP gap, $X = X(\tilde{Y})$, $X'(\tilde{Y}) > 0$. When $\tilde{Y} = 0$ retained earnings are at an equilibrium level \bar{X} . Offsetting the effect of \tilde{Y} on available resources is the impact of the GDP gap on the opportunity cost of conducting R&D (Schumpeter 1939). This is captured by allowing the economic profits associated with R&D, π , to be a function of \tilde{Y} , $\pi(\tilde{Y})$. Procyclical opportunity cost is specified with the sign of the derivative, $\pi'(\tilde{Y}) < 0$, and drives desired R&D to be countercyclical. When $\tilde{Y} = 0$ R&D profits are at an equilibrium level $\bar{\pi}$.

The amount of credit market financing, CMF, is

$$CMF = \begin{cases} \frac{\pi(\tilde{Y})^2}{2\hat{A}\psi} - X(\tilde{Y}) & R^* > X \\ 0 & otherwise \end{cases}$$

Note that in the absence of credit constraints R&D decisions are driven by changes desired R&D and are clearly countercyclical. The cyclicity of credit market financing depends on the trade-off between the output gap's impact on desired R&D $\frac{\pi(\tilde{Y})^2}{2\hat{A}\psi}$ relative to the impact on $X(\tilde{Y})$.

2.2 Credit market financing with a credit constraint

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

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

The credit multiplier, $\nu > 1$, is introduced in the specification of resources spent on R&D as follows: $\tilde{R}^* = \tilde{n}\hat{A} = \nu X(\tilde{Y})$. The value of $\nu - 1$ determines the amount of borrowing possible, as a percentage of internal resources, for a firm with retained earnings $X(\tilde{Y})$. Combining these insights produces the probability of a successful innovation under credit constraints:

$$\tilde{\mu}^* = \sqrt{\frac{2\nu X(\tilde{Y})}{\hat{A}\psi}}.$$

The amount of realized R&D, \tilde{R}^* and credit market financing for a constrained firm, \widetilde{CMF} , are:

$$\begin{aligned}\tilde{R}^* &= \nu X(\tilde{Y}) \\ \widetilde{CMF} &= (\nu - 1)X(\tilde{Y}).\end{aligned}$$

Note that the definition of desired R&D has not changed, $R^* = \frac{\pi(\tilde{Y})^2}{2\hat{A}\psi}$. Of course the level of R&D for the credit constrained firm is now determined by $\tilde{R}^* < R^*$. Realized R&D and credit market financing under a credit constraint are procyclical because $X'(\tilde{Y}) > 0$.

2.3 Output and Credit Shocks

Allow GDP to be subject to shocks, $\tilde{Y} = \delta_Y$. Additionally allow for shocks to credit markets by extending the definition of ν , $\nu = \nu(\delta_\nu)$, $\nu(0) = \bar{\nu}$. The shocks follow unspecified distributions

and are potentially correlated:

$$\begin{pmatrix} \delta_Y \\ \delta_v \end{pmatrix} \sim \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_Y^2 & \sigma_{Yv}^2 \\ \sigma_{Yv}^2 & \sigma_v^2 \end{bmatrix} \right).$$

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

$$v^* = \frac{\pi(\tilde{Y})^2}{2\psi\hat{A}X(\tilde{Y})}.$$

If $\tilde{\mu}^* < \mu^*$ it is straight forward to demonstrate that $\widetilde{CMF} < CMF$.

Figure 1 shows equilibrium in the model for two representative firms A and B. The critical value of the credit multiplier, v^* , is identified on the horizontal axis. Note that v^* is a function of δ_Y , but it is not a function of δ_v . To the left of this value, firms are credit constrained; thus, firm A in the figure is credit constrained, whereas firm B is not. The upper schedule, labeled R, determines the level of R&D spending. 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 lower schedule shows the amount of equilibrium credit market funding of R&D, which is found by subtracting X from R^* .

[Insert Figures 1 and 2 Here]

Figure 2 shows the impact of a negative output shock, δ_Y , on R&D spending. First consider firm A, the credit constrained firm. The output shock lowers retained earnings and therefore the resources the firm has available for funding R&D. This is depicted by the downward shift in the R schedule. Note that the output shock also changes the critical value of the credit multiplier, v^* , increasing the likelihood that firms will face constraints in financing. As expected R&D is procyclical for this firm and R&D falls. 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 the output shock is offset by more credit market funding of projects. Desired R&D is countercyclical, and therefore realized R&D spending is countercyclical as well. In the figure the impact of the output shock causes credit market finance to increase, $\left| \frac{2\pi(\tilde{Y})\pi'(\tilde{Y})}{2\tilde{A}\psi} \right| < X'(\tilde{Y})$.

[Insert Figure 3 Here]

Figure 3 shows the impact of a credit shock, δ_v , on R&D spending. The credit constrained firm A sees a drop in R&D because the ability to borrow has decreased even though retained earnings are unchanged. On the other hand, nothing of consequence changes for the unconstrained firm. Their level of R&D remains at the desired level and financing through credit markets remains constant.

The model highlights the potential role of output shocks on R&D through an impact on internal resources for a credit constrained firm, the role of output shocks in determining the critical value of the credit multiplier, v^* , at which firms become credit constrained, and the direct impact of credit shocks via the parameter δ_v . An empirical investigation of the relationship between R&D and the business cycle should account for the role of credit shocks and output shocks to avoid confounding the role of these shocks at the estimation stage. In the remainder of the paper, an empirical model is estimated that identifies the role of each type of shock using a panel VAR estimation strategy to uncover the dynamic relationship between R&D, output shocks, and credit market shocks, as well as assess the importance of these shocks in explaining the variation of R&D spending across advanced economies.

3 Data

The data used for this paper are combined from four sources. First, the OECD provides data on business enterprise R&D spending from 1982-2011, which dictates the time period used in

this study.² The OECD reports significant gaps in R&D spending for some countries, resulting in an unbalanced panel. A proxy for the risk premium in credit markets, measured as the spread between bank lending rates and short term treasury bills from 1982-2011, is collected from the World Bank's World Development Indicators³. Next, GDP data from 1982-2011 is available from the IMF.⁴ Finally, credit data is retrieved from an extensive new international database created by the Bank for International Settlements (BIS).⁵ The burgeoning literature on the financial cycle has typically used growth in real total non-financial private sector credit along with a proxy for housing prices (see Borio et al. (2014)). The new BIS data 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 and are denominated in local currency.

[Insert Table 1 Here]

Table 1 reports the results of panel unit root tests on the levels of our variables. The tests suggest that the levels of R&D, credit, and GDP are nonstationary variables. Therefore, our baseline panel vector autoregression model in Section 4 uses log differences of these variables. $RGDP_{i,t}$, $Credit_{i,t}$, and $R\&D_{i,t}$ are defined as the log first differenced value of country i 's GDP, credit extended to the non-financial corporate sector, and business enterprise R&D spending, respectively. The interest rate spread/risk premium, denoted $ispread_{i,t}$ is stationary. This variable is used, without differencing, with $RGDP_{i,t}$ and $Credit_{i,t}$ in constructing alternative measures of credit conditions. The final data set consists of 392 observations on 19 countries. Although the IMF classifies more than 19 countries as advanced economies, the availability of data on R&D spending limits the sample to

²http://stats.oecd.org/Index.aspx?DataSetCode=GERD_FUNDS

³<http://data.worldbank.org/indicator/FR.INR.LNDP?page=6>.

⁴<http://www.imf.org/external/ns/cs.aspx?id=28>

⁵<http://www.bis.org/statistics/credtopriv.htm>. See Dembiermont et al. (2013) for details.

these countries. Summary statistics for these variables and a list of countries included in the final data set are provided in Table 2.

[Insert Table 2 Here]

Growth in credit provided to the private sector, $Credit_{i,t}$, is the main measure of credit market conditions in this paper. Clearly, observations of credit flows represent an equilibrium outcome in credit markets and therefore represent an imperfect measure of the role of credit constraints highlighted in the model of Section 2.⁶ To complement the credit growth variable, we also incorporate information from the interest rate spread and construct the following financial conditions index:

$$fin_index_{i,t} = \frac{Credit_{i,t} - \min(Credit_{i,t})}{\max(Credit_i) - \min(Credit_i)} - \frac{ispread_{i,t} - \min(ispread_i)}{\max(ispread_i) - \min(ispread_i)},$$

where $ispread$ is the World Bank's risk spread (defined above), and $Credit$ is the growth rate in credit extended to the non-financial corporate sector. Our financial conditions index combines a country-specific percentile ranking of the credit growth and interest spread variables. The index has a maximum value of 100 (which would indicate the most rapid credit growth and most narrow interest spread) to -100 (slowest credit growth and widest interest spread).

4 Empirical Analysis

This section analyzes the cyclical behavior of annual R&D in a panel of 19 advanced economies. Although R&D data is available for a slightly wider set of countries, the sample is restricted to advanced economies (based on the IMF definition) in order to achieve a more homogeneous panel.⁷

⁶See Khan and Thomas (2013) for the importance of isolating credit shocks.

⁷Many existing studies use a sample of OECD countries. The results using the OECD sample are very similar to those reported in the paper. The IMF advanced economy sample is preferred since it provides a group of countries with similar levels of financial development.

4.1 Estimation Strategy and Results

A panel VAR is employed to evaluate the response of R&D to output and credit shocks at the macroeconomic level. A major advantage of this framework is that each variable in a VAR model is treated as potentially endogenous. The estimated model is a p th order panel VAR where p is order of the autoregressive lag. The panel VAR is specified as follows:

$$Y_{i,t} = A_1 Y_{i,t-1} + A_2 Y_{i,t-2} + \dots + A_p Y_{i,t-p} + f_i + u_t \quad (1)$$
$$i \in \{1, 2, \dots, N\}, t \in \{1, 2, \dots, T_i\}$$

The panel is defined by $N = 19$ countries (i) and a maximum of 28 years (t) per country. The vector $Y_{i,t}$ includes $k = 3$ three variables: (1) *RGDP*, (2) credit conditions $\in \{Credit, fin_index\}$, and (3) *R&D*. Note that *RGDP* and *R&D* are transformed into real growth rates and denominated in local currency. Measures of credit conditions, described above, are stationary. These variables are used to identify shocks to output and credit as suggested by the theoretical model in Section 2. The country fixed effect, f_i , absorbs cross-country variation in the mean of each macroeconomic series. In a dynamic setting, the commonly employed mean-differencing procedure would create biased coefficients on the lagged dependent variables (see Arellano and Bover (1995)). Following Love and Zicchino (2006), Helmert forward mean-differencing is implemented to estimate the dynamic fixed effects model. The individual equations are stacked and simultaneously estimated using GMM. In this process $L \geq kp$ instruments are constructed from lagged values of the $Y_{i,t}$.

Specifying a lag structure with an over identifying number of instruments allows for the determination of the optimal lag structure using a Consistent Model Moment Selection Criteria (CMMSC) based on Hansen's J statistic for over identifying restrictions (Andrews and Lu, 2001). Table 3 reports three CMMSC criteria based on the Bayesian, Akaike, and Hannan-Quinn information criteria. Using $q = 5$ lags per variable the three CMMSC statistics are calculated for lags 1 through 4. The first four rows are for the baseline panel VAR using log differences in $Credit_{i,t}$.

The next four rows test the optimal lag length for the model using $fin_index_{i,t}$. In each case the optimal lag length is unambiguously equal to one lag.⁸

[Insert Table 3 Here]

The most common means of identifying structural shocks is to employ a Choleski decomposition of the variance-covariance matrix of residuals and investigate impulse response functions. The Choleski decomposition is a recursive decomposition requiring an ordering of the variables such that contemporaneous correlation for any pair of variables is assigned to shocks in the variable ordered first. For example, the baseline ordering is: (1) output, (2) credit, (3) R&D, which assumes that output shocks have a contemporaneous impact on credit and R&D and that credit shocks have a contemporaneous impact on R&D but not output. Clearly, output and credit are highly endogenous at the macroeconomic level with feedback running in both directions. Ordering output first is appropriate because firms do not necessarily spend on capital projects immediately after obtaining credit and the full (multiplied) macroeconomic impact of credit on GDP comes with a lag. The annual frequency of the data does require a lag that is potentially problematic (a one quarter lag would be more easily defended). As it turns out, the contemporaneous correlation of the residuals from the output and credit equations in the baseline panel VAR is only 0.13, therefore the results are quite similar if credit is ordered before output.⁹

[Insert Figures 4 and 5 Here]

Figures 4 and 5 refer to panel VAR Specifications 1 and 2, respectively, and display the impulse response functions and 90% confidence intervals generated with Monte Carlo simulations.¹⁰ The first column of each figure displays the responses of each variable to a shock in output. An output

⁸As a robustness check a lag of two was also fully analyzed. The results are not significantly different from those reported in the paper.

⁹The results of this alternative ordering can be obtained from the authors upon request.

¹⁰We use 500 Monte Carlo draws to estimate the 90% confidence interval for the impulse responses. See Love and Zicchino (2006) for more information.

shock has a highly statistically significant impact on credit market conditions and R&D spending in each specification. A shock to output generates a long lived positive response of credit (consistent with findings in the credit cycle literature) and a contemporaneous impact on R&D in the same direction of the shock.

In both specifications, one observes a positive and statistically significant comovement between output and R&D induced by an output shock, which is consistent with the common finding of procyclical R&D. In a Schumpeterian world, if firms were not credit constrained, lower opportunity costs during a downturn and higher opportunity costs during expansions would induce countercyclical R&D. Our finding of procyclical responses of R&D and credit conditions to output shocks are potentially consistent with a role for credit constraints in explaining the cyclical behavior of R&D as suggested by the theoretical model in Section 2. In the theoretical model, output shocks are represented by δ_Y , which impacts the firm's retained earnings (see the shift in the R schedule in Figure 2) as well as desired R&D. For credit constrained firms, a positive output shock will relax the credit constraint by providing more internal resources to fund R&D (while negative output shocks induce a decline in internal funds and R&D). Additionally, the model tells us that a positive output shock simultaneously lowers v^* , the threshold at which credit constraints bind, and leads to both an increase in credit extended to constrained firms and an increase in R&D spending for credit constrained firms. The impulse responses in the first columns of Figures 4 and 5 provide empirical support for these mechanisms.¹¹

One of the novelties of the theoretical model in Section 2 is the separate role for credit shocks in influencing R&D, and the VAR methodology allows an empirical investigation of these shocks. The empirically identified credit shock is a proxy to the δ_v shock in the theoretical model. *Ceteris paribus*, this represents a pure stochastic innovation in credit market conditions. The lower credit multiplier reduces the availability of credit market financing for credit constrained firms, and thus

¹¹Alternatively, observed R&D may be procyclical because desired R&D is in fact procyclical as suggested by Barlevy (2007).

causes a decrease in R&D. Empirical support for the role of credit market shocks is found in the second column of Figures 4 and 5. In each specification, the credit shock has a highly statistically significant impact on R&D spending, providing further evidence that credit constraints play an important role in determining R&D on a macroeconomic level even in advanced economies where financial markets are well developed. Our finding of procyclical R&D that is sensitive to credit market conditions provides macro level support for the firm level evidence found in AABCE(2012).

It is useful to decompose the forecast error variance into the proportions due to each type of shock. The variance decompositions are reported in Table 4, which shows the percentage of long-run variation in each variable that is explained by each shock in the estimated VAR.¹² Again, results are highly consistent across specifications of the panel VAR and alternative measures of credit shocks. Here we focus on the variance decomposition for the baseline specification, Specification 1. It is common to find that a large degree of variation in a variable is due to its own innovations, but we find a considerable amount of the variation in credit market conditions is explained by output shocks. Of particular interest for this study is the third row of Table 4, where it is noted that 4.1% of the variation in R&D over a 10-year horizon is explained by output shocks and 4.3% is explained by credit shocks. In sum, roughly 8.4% of the variation in R&D is therefore attributable to cyclical conditions stemming from shocks to output and credit. Although this historical decomposition reveals a limited role for short run fluctuations in explaining R&D spending, in the next section we demonstrate that cyclical shocks are economically significant when analyzing the behavior of R&D in the aftermath of the Great Recession.

[Insert Table 4 Here]

¹²Variance decompositions at various forecast horizons and under the alternative ordering of the variables are similar to those reported in Table 4.

4.2 Application to the Great Recession

The role of credit and output shocks in explaining the cyclical nature of R&D is potentially important in assessing the costs associated with the global financial crisis, a period in which the global economy was hit by a series of output and credit shocks. In order to quantify the economic significance of the R&D response in our model, consider some back of the envelope calculations which attempt to match actual US GDP and credit growth during the Great Recession with the estimated shocks from our model. For example, US real GDP growth averaged 2.7% in our sample, but dropped to essentially zero in 2008 and -2.8% in 2009. The panel VAR estimates an orthogonalized one standard deviation shock to output at 1.6% (see top left corner of Figure 4), which suggests the US experienced roughly a one standard deviation negative output shock in 2008 (which is a conservative estimate given that output growth dropped close to zero) followed by a two standard deviation negative output shock in 2009. Similar calculations suggest the US also experienced a one standard deviation negative credit shock during 2009.¹³

[Insert Figure 6 Here]

Of particular interest for this study is the impact of these output and credit shocks on R&D. Simulating the US experience by feeding the series of negative output and credit shocks detailed above into the R&D impulse response functions yields the results (dotted blue line) displayed in Figure 6. The solid red line plots US R&D spending using the actual 2007 value and projecting a long-run average growth rate of 3.9%. Finally, the dashed green line plots actual US R&D spending for years 2007-2011. Actual US R&D spending roughly follows the pattern predicted by the impulse response functions during 2008-2010 but suffers an additional dip in 2011 (perhaps due to yet another shock). The conservative estimates produced by the model suggest that by 2011 R&D falls \$26 billion below its pre-crisis path and that a permanent R&D gap of 10% has opened

¹³US credit growth averaged 4.2% in our sample, but dropped to approximately zero in 2009 and -2.5% in 2010. The estimated impact of the output shocks in 2008 and 2009 on subsequent credit growth combined with a one standard deviation shock to credit itself in 2009 would roughly generate the observed pattern in credit.

up between pre- and post-crisis R&D.¹⁴ This economically significant drop in the level of R&D suggests a channel through which the Great Recession could significantly damage long-run growth prospects. Estimating the impact on long-run potential supply is beyond the scope of this paper, but the results provide support for the estimates provided by Reifschneider et al. (2013) and the concerns about stagnation registered by Summers (2014).

5 Conclusion

This paper makes a number of significant contributions to the existing literature. First, it focuses on the cyclical behavior of R&D at the macro level using data that includes the recent financial crisis, while most existing studies use firm or industry level data. Second, this paper jointly models the time series behavior of output, credit, and R&D using a panel VAR. The primary empirical findings can be summarized as follows: (1) R&D responds pro-cyclically to output shocks at the macroeconomic level, and (2) R&D co-moves positively with credit. More concretely, the results indicate that negative output shocks induce a simultaneous and subsequent contraction in credit and R&D consistent with a model where credit constraints drive cyclical adjustments to R&D. In addition the results indicate an independent impact of credit shocks directly on R&D. The impact of output and credit shocks on R&D are economically significant and a simple simulation exercise conservatively estimates that the shocks associated with the global financial crisis have reduced US R&D spending by 10% relative to the pre-crisis path. In sum, the empirical evidence is strongly consistent with an important role for credit conditions in explaining the cyclical behavior of R&D, perhaps surprisingly strong evidence given that the sample is restricted to advanced economies with the world's most sophisticated financial systems.

¹⁴The R&D gap is permanent because R&D exhibits a unit root as described in Section 3.

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Figure 1: Equilibrium and Credit Constraints

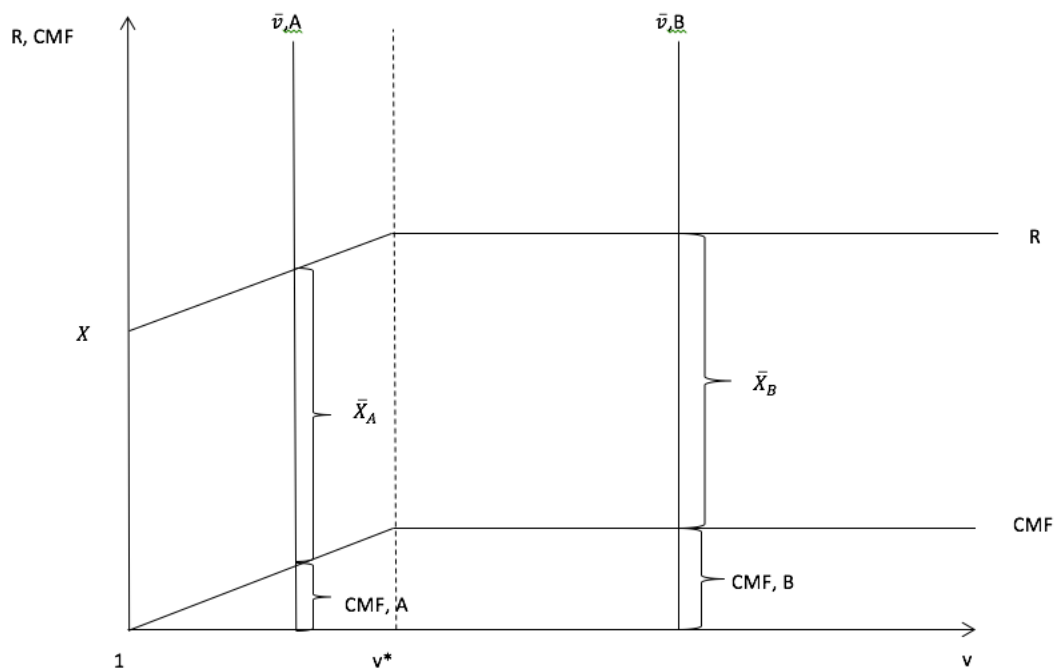


Figure 2: Output Shock

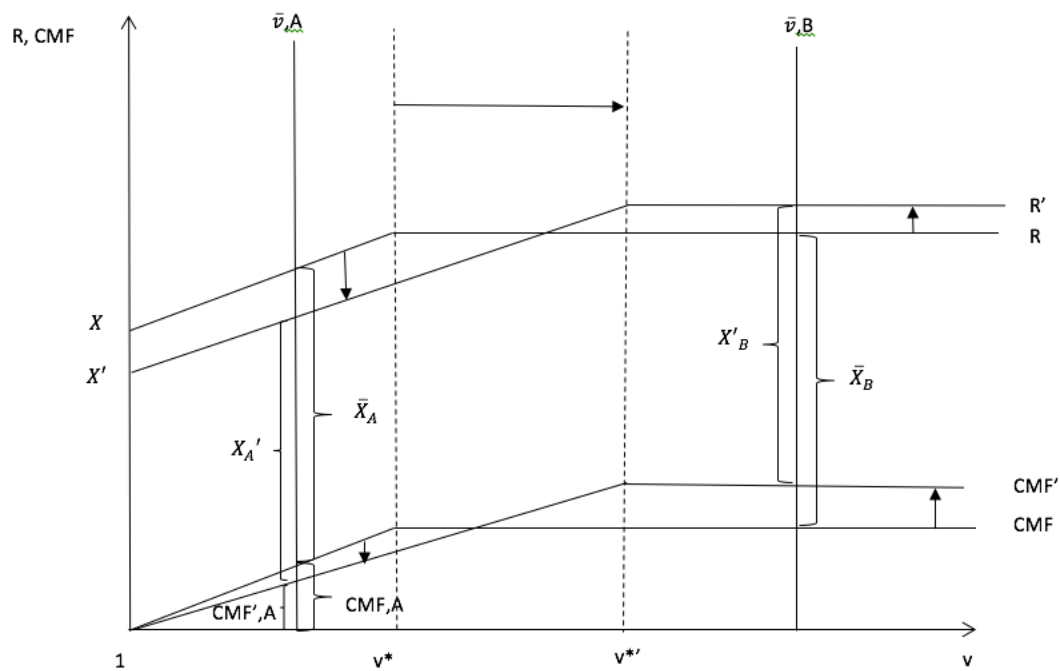


Figure 3: Credit Shock

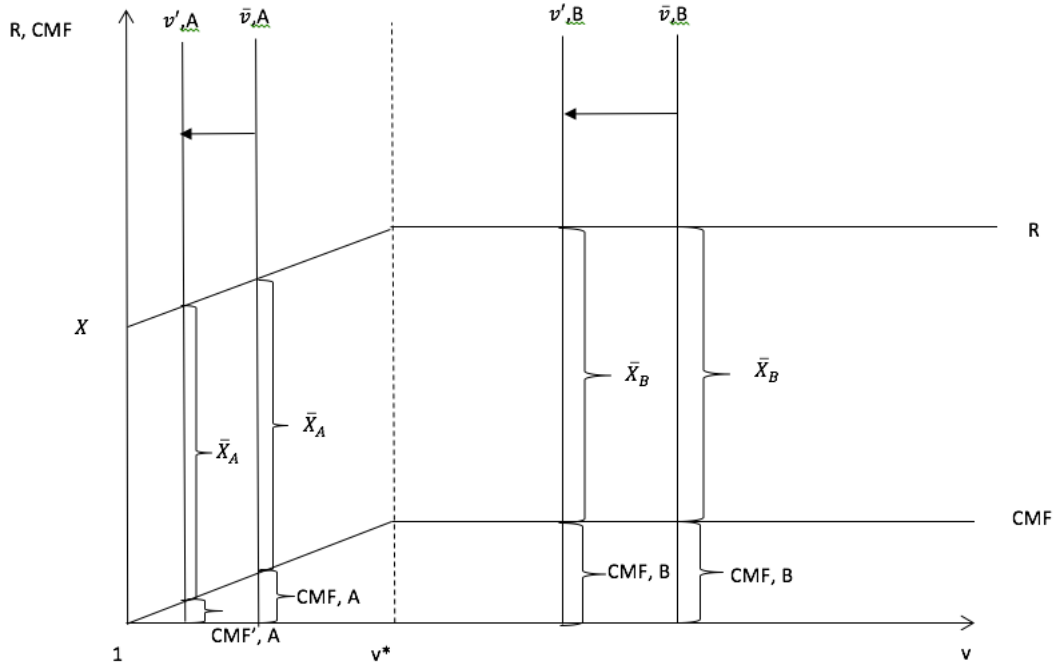


Figure 4: Impulse Response Functions (Specification 1)

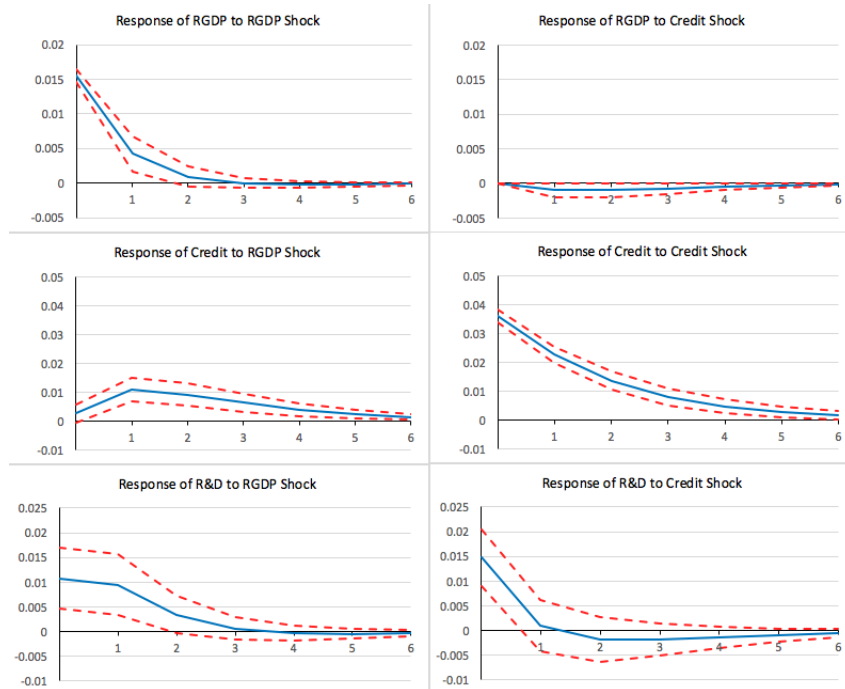


Figure 5: Impulse Response Functions (Specification 2)

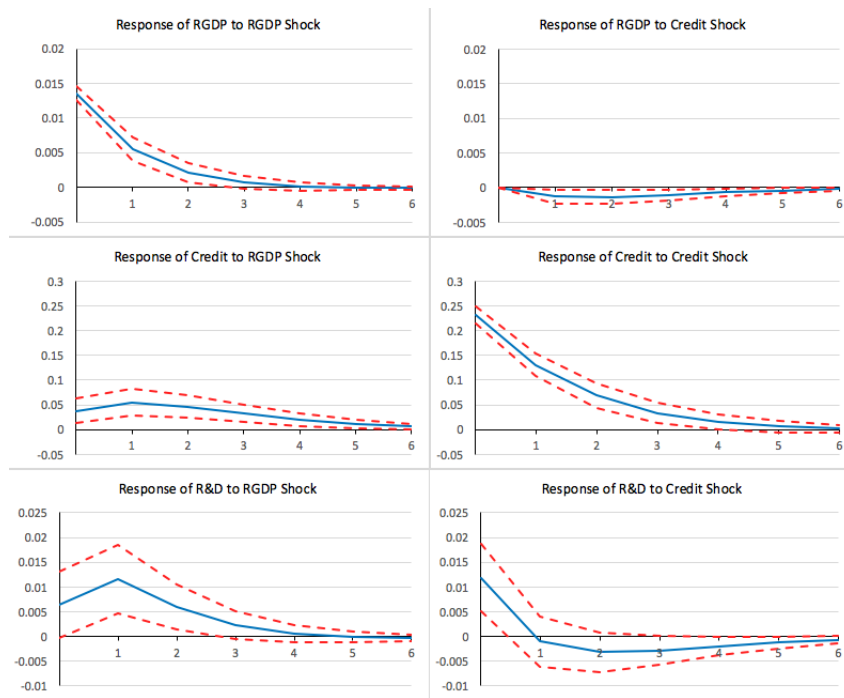


Figure 6: Great Recession R&D Gap

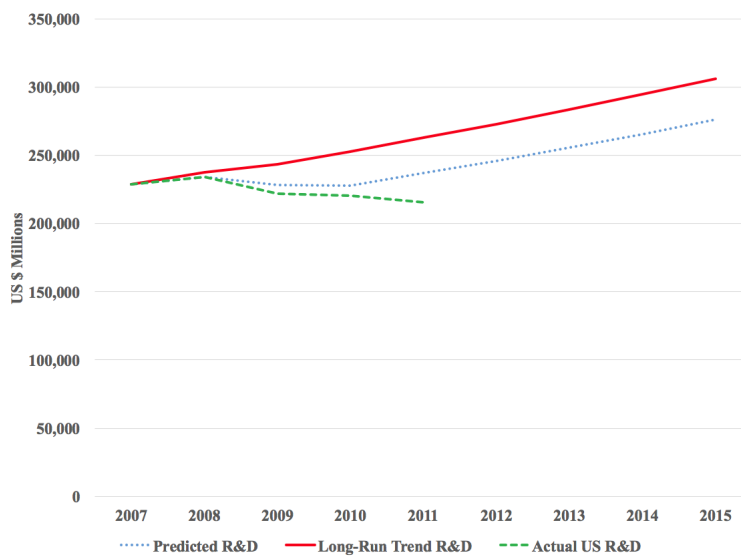


Table 1: Unit Root Tests

	Statistic	P-Value
Real GDP	1.011	(0.844)
R&D	1.330	(0.908)
Credit	3.224	(0.999)
Interest Rate Spread	-4.272	(0.000)
Financial Conditions Index	-4.225	(0.000)

Phillips-Perron unit root test with inverse normal test statistic reported. Null hypothesis is all panels contain unit roots. Alternative hypothesis is at least one panel is stationary. Time trends included for GDP, R&D and Credit. Panel means and two lags are included for all variables.

Table 2: Summary Statistics

	N	$RGDP_{i,t}$		$Credit_{i,t}$		$R\&D_{i,t}$		$ispread_{i,t}$	
		Mean	(Std. Dev.)	Mean	(Std. Dev.)	Mean	(Std. Dev.)	Mean	(Std. Dev.)
All 19 Countries	392	0.025	(0.026)	0.041	(0.054)	0.052	(0.081)	2.720	(1.869)
Australia	26	0.033	(0.014)	0.048	(0.065)	0.091	(0.088)	3.329	(0.629)
Belgium	26	0.019	(0.016)	0.053	(0.048)	0.027	(0.048)	3.879	(1.418)
Canada	30	0.025	(0.022)	0.032	(0.038)	0.039	(0.074)	1.645	(0.371)
Czech Republic	15	0.027	(0.030)	0.006	(0.066)	0.062	(0.110)	2.934	(1.609)
Denmark	8	0.008	(0.030)	0.012	(0.029)	0.085	(0.075)		
Finland	14	0.024	(0.036)	0.045	(0.035)	0.054	(0.068)		
France	29	0.018	(0.015)	0.038	(0.032)	0.033	(0.034)	1.733	(1.563)
Germany	16	0.014	(0.022)	0.023	(0.037)	0.033	(0.036)	6.063	(0.550)
Ireland	9	0.018	(0.042)	0.106	(0.080)	0.034	(0.067)		
Italy	29	0.015	(0.019)	0.032	(0.040)	0.025	(0.069)	3.116	(1.422)
Japan	29	0.021	(0.026)	0.024	(0.050)	0.041	(0.057)	2.122	(0.669)
Korea	15	0.044	(0.038)	0.055	(0.066)	0.075	(0.075)		
Netherlands	8	0.031	(0.012)	0.042	(0.028)	0.032	(0.061)		
Norway	9	0.021	(0.025)	0.065	(0.058)	0.076	(0.086)		
Portugal	28	0.024	(0.025)	0.032	(0.060)	0.101	(0.132)	6.787	(2.153)
Singapore	16	0.056	(0.043)	0.050	(0.085)	0.091	(0.150)	4.282	(0.858)
Spain	29	0.027	(0.021)	0.050	(0.058)	0.067	(0.086)	1.373	(1.871)
United Kingdom	26	0.026	(0.023)	0.059	(0.065)	0.017	(0.049)	0.303	(0.262)
United States	30	0.027	(0.020)	0.042	(0.039)	0.039	(0.046)	3.044	(0.448)

Notes: $RGDP_{i,t}$ is the log first differenced value of country i 's GDP.

$Credit_{i,t}$ is the log first differenced value of credit extended to non-financial corporate sector in country i .

$R\&D_{i,t}$ is the log first differenced value of business enterprise R&D spending in country i .

Table 3: Optimal Lag Selection

# of lags	MBIC	MAIC	MQIC
Specification 1			
1	-171.712	-40.097	-92.852
2	-128.562	-29.850	-69.417
3	-83.432	-17.624	-44.002
4	-42.688	-9.784	-22.973
Specification 2			
1	-149.139	-28.987	-77.570
2	-114.831	-24.717	-61.154
3	-78.305	-18.229	-42.520
4	-38.712	-8.674	-20.820

Note: $MBIC = J - (|q| - |p|)k^2 \ln(n)$, $MAIC = J - 2(|q| - |p|)k^2$, and $MQIC = J - R(|q| - |p|)k^2 \ln(n)$. In each case, J is Hansen's J for over identification.

Table 4: Variance Decomposition (10 Year Horizon)

Specification 1				
		Shocks to:		
		$RGDP_{i,t}$	$Credit_{i,t}$	$R\&D_{i,t}$
Variation in:				
	$RGDP_{i,t}$	0.987	0.010	0.003
	$Credit_{i,t}$	0.115	0.884	0.000
	$R\&D_{i,t}$	0.041	0.043	0.915
Specification 2				
		Shocks to:		
		$RGDP_{i,t}$	$fin_index_{i,t}$	$R\&D_{i,t}$
Variation in:				
	$RGDP_{i,t}$	0.972	0.023	0.006
	$fin_index_{i,t}$	0.097	0.896	0.007
	$R\&D_{i,t}$	0.044	0.035	0.921