Paper to be presented at

DRUID15, Rome, June 15-17, 2015

(Coorganized with LUISS)

On the Cyclicality of R&D Investments in the Presence of Financial Constraints and R&D Subsidies

Hanna Hottenrott
Heinrich Heine University Duesseldorf
Duesseldorf Institute for Competition Economics (DICE)
hottenrott@dice.hhu.de

Tianyu Zhang
Heinrich-Heine-Universität Düsseldorf
DICE
zhang@dice.hhu.de

Abstract

The Schumpeterian view of the business cycle suggests that the opportunity cost of long-term investments, like Research & Development (R&D), is lower during recessions. This implies that firms expand long-term investments in downturns and favor short-run investments in booms. Observing private-sector R&D spending during recent years across the globe, however, does not support this theory.

This papers studies the influence of financial frictions and government stimulus on private sector R&D investment over the business cycle. Building on a theoretical model which takes into account the complementarity between R&D and other investments as well as imperfect capital markets and government subsidies, we show that the presence of credit constraints turns R&D more pro-cyclical, while R&D subsidies have the opposite effect. We test the theoretical predictions using firm-level data for Germany for the period 1994 to 2010 and find that without binding credit constraints, R&D investment tends to be counter-cyclical. The more binding the credit constrained, the more pro-cyclical it gets. Moreover, large or subsidized firms' R&D investment is not sensitive to sales shocks while non-subsidized SMEs are most sensitive to the business cycle.

Jelcodes:O31,O32

On the Cyclicality of R&D Investments in the Presence of Financial Constraints and R&D Subsidies[*]

Hanna Hottenrott[1] *and Tianyu Zhang*[2]

ABSTRACT
The Schumpeterian view of the business cycle suggests that the opportunity cost of long-term investments, like Research & Development (R&D), is lower during recessions. This implies that firms expand long-term investments in downturns and favor short-run investments in booms. Observing private-sector R&D spending during recent years across the globe, however, does not support this theory. This paper studies the influence of financial frictions and government stimulus on private sector R&D investment over the business cycle. Building on a theoretical model which takes into account the complementarity between R&D and other investments as well as imperfect capital markets and government subsidies, we show that the presence of credit constraints turns R&D more pro-cyclical, while R&D subsidies have the opposite effect. We test the theoretical predictions using firm-level data for Germany for the period 1994 to 2010 and find that without binding credit constraint is, R&D investment tends to be counter-cyclical. The more binding the credit constraint is, the more pro-cyclical R&D gets. Moreover, large or subsidized firms' R&D investment is not sensitive to sales shocks while non-subsidized SMEs are most sensitive to the business cycle. In addition, we study two natural experiments, the EU enlargement in 2004 and the economic crisis in 2008, to test the effects of exogenous sales shock on R&D. Employing a synthetic control group method (Abadie and Gardeazabal 2003, Abadie, Diamond and Hainmueller 2010) and using weighted averages from non-exporting firms as control group, we find that among exporting firms the effect of credit constraints on pro-cyclicality only holds for the negative shock of 2008, while R&D investments decrease during period of sales booms.

KEYWORDS — Research and Development, Business Cycle, Liquidity Constraints, Innovation Policy
JEL CODES — O31, O32, O38

THIS VERSION — May 2015, PRELIMINARY

[*]The authors thank ZEW for providing the MIP data and participants of the PhD seminar at DICE for helpful comments.

[1]Corresponding author . Düsseldorf Institute for Competition Economics (DICE), Universitätstr. 1, 40225 Düsseldorf, Germany. Tel: +49(0)2118110266, fax: +49(0)2118115499. E-mail: hottenrott@dice.hhu.de

[2]Düsseldorf Institute for Competition Economics (DICE), Universitätstr. 1, 40225 Düsseldorf, Germany. E-mail: zhang@dice.hhu.de

1 Introduction

Since Schumpeter's view of the business cycle it is argued that opportunity cost of long-term investments, like R&D, is lower compared with that of short-term investment during recessions. This should make long-term investments more attractive during downturns. Thus, R&D activities in the private sector should expand during recessions and shrink in booms. While there has been theoretical support for this idea (Hall 1992, Aghion and Saint-Paul 1998, Bloom 2007), the empirical literature paints a different picture.[1]

Studies find pro-cyclical R&D investments in different countries and over different time periods. For instance, Geroski (1994) studies macro-level UK data over the period 1948 to 1983 and finds pro-cyclical patenting and innovation both in terms of commercial success and technological breakthrough. Waelde and Woitek (2004) look at a broader country-level data from G7 during 1973 to 2000 period and observe pro-cyclical R&D spending. Barlevy (2007) also shows that aggregate R&D investment in the U.S. during 1987 to 2004 behaved rather pro-cyclical and develops a dynamic theoretical model which explains pro-cyclical R&D investment by the short-sighed entrepreneurs. R&D investment may also be a-cyclical. For instance, Saint-Paul (1993) uses panel data for 22 OECD countries over 1950 to 1988 and finds no significant correlation between firm-financed R&D and sales shocks.

In search for explanations for these mixed results, studies increasingly explore the role of firm heterogeneity and in particular their access to finance long-term investments. One basic assumption of the simple business cycle models is that firms can finance their R&D expansion in down-turns. Building on previous research that showed that firms' R&D spending relies more on internal funding than other types of investment (Hall 1992, Himmelberg and Petersen 1994, Rafferty 2003). Czarnitzki and Hottenrott (2011b) argue that because of this cash flow effect, R&D investment tends to be pro-cyclical if firms financing

[1]Gali and Hammour (1992) examine U.S. data and find a negative correlation between productivity and sale shocks and this evidence implicitly implies that some productivity-boosting investment or 'human capital' investment should also be counter-cyclical.

their R&D internally. Aghion, Askenazy, Berman, Cette and Eymard (2012), Domadenik, Prasnikar and Svejnar (2008) and Lopez-Garcia, Montero and Moral-Benito (2012) indeed propose that financial frictions prevent firms from investing on long-term projects in rough times, thus stimulating credit constrained firms to investment more in booming periods. Especially small- and medium-sized enterprises (SMEs) often lack overall collateral value to back loans for intangible investments as R&D which makes them particularly dependent on internal financing (Czarnitzki and Hottenrott 2011a). Sharpe (1994) shows that SMEs are more responsive to the recession and according to Gertler and Gilchrist (1994) small firms act stronger to monetary policy changes.

With capital market failure to provide financing for all innovative projects in mind, governments try to foster R&D in the economy by providing R&D subsidies. In several OECD countries, direct grant-based subsidies for R&D are common, but their role for smoothing firms' R&D investment over the business cycle remains largely unexplored.

This paper extends previous work in several ways. First, we set up a simple model which captures the basic characteristics of R&D activities by differentiating between short-term and long-term investment. More specifically, R&D activities benefit firms through making their short-term investment more efficient. In terms of empirical implementation, we follow (Czarnitzki and Hottenrott 2011a, Czarnitzki and Hottenrott 2011b) and use a direct measure for access to external financing which is the firms' credit rating. Third, we also take grant-based subsidies into consideration which are the most common innovation policy tool in Germany[2] and many other countries. Aggregate R&D investment in Germany show neither a clear pro- nor counter-cyclical pattern (see Figure 2) suggesting considerable firm heterogeneity. Estimating fixed-effects and dynamic panel data models, we find that without credit constraint or subsidies, counter-cyclical patterning dominates. Credit constraints drive R&D investment more pro-cyclically while subsidies make it more a-cyclical. Large, deep-pocket firms do not show any cycle-sensitivity pattern.

In addition, we study two natural experiments, the EU enlargement in 2004 and the

[2]There are no R&D tax credits in Germany.

economic crisis in 2008, to test the effect of an exogenous sales shock on R&D. While the former constituted a positive sales shock to exporters, the latter was clearly related to a negative one. Employing a synthetic control group method (Abadie and Gardeazabal 2003, Abadie et al. 2010) and using weighted averages from non-exporting firms as control group, we find that among exporting firms the effect of credit constraints on pro-cyclicality only holds for the negative shock of 2008, while R&D investments decrease during period of sales booms. These results point to the importance of credit constraints during periods of recession.

The paper proceeds as follows. In the next section, we propose a simple model to explore the relationship between R&D investment and the business cycle. Section III describes our data, measurements, descriptive statistics and results. Discussion and conclusion follow in section IV.

2 Theoretical framework

2.1 Benchmark model

In the following, we consider one representative risk-neutral firm that maximizes its profits given the market demand. First, we set up a benchmark model where there are no credit constraints nor R&D subsidies. Without credit constraints, the firm is always able to collect enough financing from capital markets (loans or equity) to support its short and long-term investment.

The demand comes from a Markov process, which is widely used in the literature.[3] Assume that the firm faces exogenous demand shocks denoted by a_t. Then the demand shock in the next stage is given based on the current shock plus a random disturbance

[3] Another common way to model the uncertainty is to use Geometric Brownian motion with a shift and volatility term as in (Barlevy 2007). However, in order to get closed-form solution, we choose the first form.

with a mean assumed to be zero. We can simply express this as:

$$Ea_{t+1} = a_t^{\rho} \tag{1}$$

where ρ represents the persistence in exogenous demand. Given that ρ lies between 0 and 1, we design a recurrent economic situation. This simply suggests that if the firm faces a large a_t at t period, either negative or positive, the rational expectation for t+1 period is that the shock will be milder. This assumption is of importance to our future analysis and has its practical ground, since no normal economy can be always booming or always in recession.

The model has two stages and the net present value is simply the sum of profit generated in two periods. At $t = 0$, the firm has to make its decision on how much to investment on both short-term (k_t) and R&D investment (z_t). Consider the short-term investment to be like the establishment of a fixed production line or machine and once this capital investment is made, we cannot adjust the size or scale of it in the second stage. Once the production line is set, it produces goods at the end of the first stage, following a neo-classic production function $p(k)$. This simply means that $p' > 0 > p''$. In order to render explicit solution, we assume $p(k)$ takes the form of $(k_t)^{\alpha}$, with $\alpha \in (0, 1]$. However the firm's profit does not only rely on production, but also the economic situation, namely a_t. When the demand shock a_t is positive, the total demand for that product increases, which leads to higher profit, and vice versa.

The profit function derived from the first stage is thus:

$$\pi_t = a_t p(k_t) \tag{2}$$

R&D investment, on the other hand, plays a complementary role as it does not generate any profit alone. This seems reasonable to assume as R&D is usually the investment in know-how which then needs to be applied in the production of goods and services.

During the first stage, after the investment decision is made, the R&D project thus facilitates the productivity of the fixed production line in the second stage. Put differently, the R&D decision does not effect output until second stage. Then the productivity of R&D investment is captured by $q(z_t)$. Thus, the profit function from the second stage has three elements: expected demand shock Ea_{t+1}, production function $p(k_t)$ and the benefit from R&D investment $q(z_t)$,

$$\pi_{t+1} = Ea_{t+1}p(k_t)q(z_t) \tag{3}$$

For reasons of simplicity, we impose a functional form on q, that is $q(z_t) = e\sqrt{z_t}$. Here, e represents the exogenous efficiency of R&D research and for R&D investment to be efficient, we add another assumption, $e\sqrt{z_t} > 1$. Using backward induction, our target is to:

$$\Pi = a_t p(k_t) + Ea_{t+1}p(k_t)\sqrt{z_t} \tag{4}$$

subjected to

$$k_t + z_t \leq \omega_t \tag{5}$$

It is straightforward to see that the budget constraint will always be binding, i.e. firms will exhaust their budget since there is no available outside option. The optimal R&D share therefore is represented as follows:

$$R\&Dshare_{bk} = \frac{\omega(1+2\alpha)e^2a^{2\rho} + 2a^2\alpha^2 - 2a\alpha\sqrt{\omega(1+2\alpha)e^2\alpha^{2\rho} + a^2\alpha^2}}{a^{2\rho}e^2(1+2\alpha)^2\omega} \tag{6}$$

If we take the derivative of the optimal R&D share with respect to demand shock a_t, we get negative sign, which leads to our first Hypothesis:

H1: Within benchmark setting, share of R&D investment in a firm's total investment is counter-cyclical.

The intuition behind this is quite straightforward. When faced with an up-turn, firms would be better-off to grasp the benefit at present and delay the R&D investment until the economy is not behaving that well. In addition, the sign for the first order condition of R&D share with respect to budget size ω is positive. Hence, we hypothesize, that

H2: More available internal fund leads to higher R&D share in a firm's total investment.

This corresponds to the traditional pecking order theory and transaction cost theory, which predict that because of the characteristics of R&D investment, internal funds are first source to be considered. When firms exhaust their internal funding, they consider borrowing.

2.2 In the presence of credit constraint

Within the same setting, we analyze the effect of credit constraints by introducing the parameter μ. Compared to non-credit constrained firms, those constrained ones have only $\mu\omega_t$ amount of budget at their disposal. Using the same reasoning, we derive at the R&D share in the presence of credit constraint,

$$R\&Dshare_{withCS} = \frac{\mu\omega(1+2\alpha)e^2a^{2\rho} + 2a^2\alpha^2 - 2a\alpha\sqrt{\mu\omega(1+2\alpha)e^2\alpha^{2\rho} + a^2\alpha^2}}{a^{2\rho}e^2(1+2\alpha)^2\mu\omega} \tag{7}$$

Again, we have a negative FOC for R&D share with respect to demand shock. This means, in principal, credit constraint does not change the counter-cyclical pattern of R&D investment. However, we can show that when $\frac{2a^2\alpha^2(1+\sqrt{2})}{e^2\omega(1+2\alpha)a^{2\rho}} > 1$, for any $\mu \in (0,1]$, we have $\frac{\partial^2 R\&Dshare}{\partial a_t \partial \mu} < 0$. This conclusion simply tells us that with tighter credit constraint, in other words, smaller μ, we should have larger $\frac{\partial R\&Dshare}{\partial a_t}$. However, in general, we still get negative sign, the effect of credit constraint is to make the R&D investment less counter-cyclical:

H3: Binding credit constraints reduce the counter-cyclicality of R&D investment.

The intuition behind this result is the following. While because of lower opportunity cost, it is efficient for a firm to invest in R&D during recession period, the credit constraint limits the firm's ability to finance the expansion in absence of available external funding. Firms will therefore expand less than in absence of the constraint during recession and expand more during periods that provide them with more cash.

2.3 In the presence of R&D subsidies

In the same vein, we analyze the effect of R&D subsidy. We assume, besides $\mu\omega$, firms that are subsidized have now access to another s part of their own budget. This extra part of budget can be multiplicative or additive. Both render qualitatively similar result. Now, subsidized firms have $\mu\omega(1+s)$ in total. After taking the first derivative of R&D share with respect to demand shock, we still have counter-cyclical R&D investment. However, when $\frac{2a^2\alpha^2(1+\sqrt{2})}{e^2\mu\omega(1+2\alpha)a^{2\rho}} > 1$ holds, we can prove that for $s \in (0, \frac{2\alpha^2(1+\sqrt{2})a^{2-2\rho} - e^2(1+2\alpha)\mu\omega}{e^2\mu\omega(1+2\alpha)})$, we have $\frac{\partial^2 R\&Dshare}{\partial a_t \partial s} < 0$. We believe no firm gains access to an infinite amount of subsidy, so the upper bound of s has its practical ground here. This result suggests that an R&D subsidy would decreases derivative $\frac{\partial R\&Dshare}{\partial a_t}$. Combined with the fact that the sign remains to be negative, we should have more counter-cyclical R&D investment in the presence of R&D subsidy, which motivates constrained firms to invest more counter-cyclically and reduces, to some extent, the efficiency loss caused by credit constraint. Thus, the fourth hypothesis is:

H4: R&D subsidy makes R&D more counter-cyclical.

3 Empirical approach

3.1 Data

The main data for the following analysis stems from the Mannheim Innovation Panel (MIP) conducted by the Center for European Economic Research (ZEW). The MIP is constructed from repeated cross-sections which are part of the European Community Innovation Survey. The survey is conducted annually and it is sampled such that it is representative for firms with more than five employees in services and manufacturing sectors.[4] We complement the MIP data with the credit rating index from the Credit-reform database[5]. We focus the present study on firms located in Western Germany. Even though reunification happened before our sample period, there still exists structural difference in terms of firm size, R&D investment, wages and innovation input that complicate a joint analysis difficult. More importantly though, there have been huge governmental programs to restructure and rebuild Eastern Germany that are likely to make the region immune against normal business cycles. After elimination of incomplete records and outliers we have full information on 5,126 firm-level observations. Almost 60% percent of observations are from SMEs. So our sample is more representative in that, compared to previous literature which is only restricted to large firms, we have various types of firms included.

3.2 Econometric specification

We estimate different panel data models taking into account unobserved heterogeneity serial and correlation. In particular, we estimate models that - in its simplest form - can be

[4]See Table 4 in the Appendix for details on the industry distribution.

[5]See Czarnitzki and Hottenrott (2011b) for a detailed description on the construction of the index.

written such that:

$$ratioRD_{i,t} = \beta_1 \triangle Sales_{i,t} + \beta_2 CreditConstraint_{i,t} + \beta_3 \triangle Sales_{i,t} \times CreditConstraint_{i,t} + \beta_4 PCM_{i,t} + Year + Industry + \tau_i + \epsilon_{i,t} \tag{8}$$

According to the theoretical analysis above, we expect β_1 to be negative, while β_3, β_4 to be positive. The dependent variable, the R&D in a firm's total investment, is the ratio $\frac{R\&Dinv_{i,t}}{R\&Dinv_{i,t}+Capinv_{i,t}}$ in t period. It measures the intensity of R&D investment and corresponds to the expression in our theoretical model. R&D investment is computed as total expenditure on innovation. Capital investments include physical, non-innovation related investment. We measure a firm's specific sales shock as the change in log value of sale between two periods. That is,

$$\triangle Sales_{i,t} = ln(\frac{Sales_{i,t}}{Sales_{i,t-1}}) = ln(Sales_{i,t}) - ln(Sales_{i,t-1}) \tag{9}$$

From above, we can tell the change of $\triangle Sales$ captures the $a_t^{1-\rho}$, which is positively correlated with a_t. The credit rating index ranges from 100 to 600, with 100 being the best and 600 the worst. This rating has the advantage that (i) it is continuous and therefore contains more information than dichotomous measure and (ii) this score is calculated by taking into account the future conditions of firms and gets updated on regularly basis by rating institute and is in fact used by banks, customers and suppliers when deciding to engage with a certain firm. The subsidy receipt is measured by a dummy variable stemming from MIP and captures whether a firm received a subsidy from regional, national or supranational bodies (e.g. the EU). We also control for internal funding. Since accounting data is unavailable for the firms in our sample, we calculate the firms' empirical price cost margins based on their sales, intermediate inputs and personnel costs obtained from the MIP. To liquidity accrued in the last period, we use the lagged $PCM_{i,t}$ as our measurement.

$$PCM_{i,t} = \frac{Sales_{i,t} - StaffCost_{i,t} - MaterialCost_{i,t} + \delta R\&D_{i,t}}{Sales_{i,t}} \tag{10}$$

Finally, we add year dummy variables and industry dummy variables to control for time and sector fixed effects. It should be noted that we allow firms to move between sectors over time.

The descriptive statistics of full sample, large firms sub-sample and small firms sub-sample are provided in Table 1.[6] In line with the definition of the European Commission,

Table 1: Descriptive Statistics

Variable name	**units**	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**T-value**
Overall sample (5,126 observations)						
$R\&Dintensity$	Ratio	0.284	0.32	0	1	
$\triangle Sales$	Log	0.031	0.35	-5.39	41734,00	
$CreditConstraint$	Index [100,600]	208.12	53.72	100	600	
$\triangle Sale * CreditConstraint$	multiply	5.58	79.21	-1300.8	1173.5	
$Subsidy$	dummy	0.284	0.45	0	1	
PCM	log	0.21	3.3	-165.62	1.35	
sme	dummy	0.57	0.5	0,00	1,00	
Small firms (2,917 observations)						
$R\&Dintensity$	Ratio	0.3	0.336	0	1	
$\triangle Sales$	Log	0.007	0.332	-5.4	2.48	
$CreditConstraint$	Index [100,600]	225.7	50.42	101	600	
$\triangle Sales * CreditConstraint$	multiply	1.54	80.8	-1300.8	589.1	
$Subsidy$	dummy	0.275	0.446	0	1	
PCM	log	0.17	4.36	-165.6	1.35	
Large firms (2,209 observations)						
$R\&Dintensity$	Ratio	0.255	0.282	0	1	-5.25***
$\triangle Sales$	Log	0.061	0.37	-4.0	5.4	5.39***
$CreditConstraint$	Index [100,600]	185,00	48.95	100	600	-29.03***
$\triangle Sales * CreditConstraint$	multiply	10.93	76.75	-1098.8	1173.5	4.21***
$Subsidy$	dummy	0.295	0.456	0	1	1.53*
PCM	log	0.264	0.32	-10.83	1.12	1.21

we categorize firms that employ less than 250 people as SMEs. According to this criteria, we have 2,917 SME-observations and 2,209 large firm-observations in the sample. As can be seen from Table 1, these firms differ in the key variables of the sample. We add the t-value test for differences in variable means in the last column. From the t-test, in general:

1. SMEs invest more in R&D relative to their total investments than larger firms, although higher R&D-shares do not necessarily mean that the absolute number of

[6]See Table 5 for a cross-correlation matrix

R&D investment is also higher.

2. Larger firms have more volatile sales than SMEs.

3. SMEs have higher (i.e. worse) credit ratings. This finding also conforms to the theory which suggests that the SMEs lack hard collateral and, because of asymmetric information problem, are more likely to be credit constrained.

4. Larger firms more often receive a subsidy.

3.3 The results

Table 2 shows the main regression results.

We first focus on the results from the fixed effects panel models. According to the Hausman test the Chi^2 value is 123 (Prob>chi2=0.00) suggesting the presence of unobserved heterogeneity. For the full sample, the counter-cyclical patterning (i.e. the coefficient of $Sales_{i,t}$ and its lagged terms are always negative). This confirms Hypothesis 1. While the credit constraint measure is not significant itself, the interaction term $\Delta Sales_{i,t} * CreditConstraint_{i,t}$ is positive and significant. This suggests that the worse the credit rating is, the more pro-cyclical the R&D investment becomes. This confirms Hypothesis 3.

Hypothesis 2 is also confirmed by the positive coefficient of $PCM_{i,t}$. We introduce this variable in column two. This positive correlation indicates that the more internal capital a firm has access to, the more it will be engaged in the R&D investment, which is in line with previous research implying a positive elasticity of R&D to internal financing. The size and statistical significance of $\Delta Sales$ and of interaction term do not change because of the introduction of PCM. It should be noted that these results are robust to the definition of the credit constraint and hold when using a dichotomous credit constraint indicators (as in Aghion et al 2012). For the sake of comparison, we also list out the main results in Aghion et al (2012) in Table 6 for comparison.

Table 2: Regression Results on Full Sample

Variables	FE(Without PCM)	FE(With PCM)	Panel Tobit (RE)	Dynamic panel Tobit(RE)	Dynamic panel
$DepVar_{i,t-1}$				0.561***	0.204***
				(0.034)	(0.04)
$DepVar_{i,t-2}$					0.038
					(0.056)
$\Delta Sales_{i,t}$	-0.096***	-0.11**	-0.15**	-0.233**	-0.345***
	(0.028)	(0.038)	(0.06)	(0.097)	(0.13)
$\Delta Sales_{i,t-1}$					-0.37***
					(0.124)
$\Delta Sales_{i,t-2}$					-0.3**
					(0.124)
$\Delta Sales_{i,t} * CreditConstraint_{i,t}$	0.0004***	0.0005**	0.0007***	0.0012***	0.0012**
	(0.0001)	(0.0002)	(0.0002)	(0.0004)	(0.0005)
$\Delta Sales_{i,t-1} * CreditConstraint_{i,t-1}$					0.0013**
					(0.0006)
$\Delta Salesi, t-2 * CreditConstraint_{i,t-2}$					0.0013**
					(0.006)
$PCM_{i,t}$		0.002***	0.0015	0.1***	0.115*
		(0.0005)	(0.0023)	(0.03)	(0.063)
$PCM_{i,t-1}$					-0.03
					(0.073)
$PCM_{i,t-2}$					-0.039
					(0.045)
$CreditConstraint_{i,t}$	-0.00013	-0.0002	-0.0001	-0.0002	-0.0000
	(0.000)	(0.0001)	(0.0002)	(0.0003)	(0.0004)
$ln(FirmAge)_{i,t}$			-0.14***	-0.134***	
			(0.04)	(0.046)	
$[ln(FirmAge)]^2_{i,t}$			0.025***	0.023***	
			(0.08)	(0.007)	
$MEAN[\Delta Sales]_i$			0.589***	0.397**	
			(0.21)	(0.2)	
$MEAN[CreditConstraint]_i$			-0.0003	-0.0003	
			(0.0002)	(0.003)	
$MEAN[\Delta Sales * CreditConstraint]_i$			-0.002**	-0.0014*	
			(0.001)	(0.0008)	
$MEAN[PCM]_i$			-0.0007	-0.01**	
			(0.004)	(0.004)	
$MEAN[ln(FirmAge)]_i$			-0.07***		
			(0.026)		
$Constant$	0.15	0.2***	0.587**	0.334*	—
	(0.11)	(0.07)	(0.2)	(0.178)	
Overall significance	3.46	3.36	1011.8	1481.82	301.9
Joint significance of time	7.01***	2.1***	160.5***	56.42***	
Joint significance of industry	1.22	42.7***	714.48***	423.04***	
Joint significance of means			17.17***	13.08**	
AR(1)					-4.6***
AR(2)					-0.126
Sargan-test (chi2)					330.1
Number of obs	8,492	5,126	3,479	5,191	1,943

Notes: ***,** ,* indicate a significance level of 1%, 5%, 10%. The models include a constant and 29 industry dummies.
Robust standard errors in parentheses.

In the third column we perform panel tobit model, considering that our dependent variable is bounded between 0 and 1. The sign of sales shock, interaction term and price cost margin is very close to the fixed effect OLS panel model, and size of the coefficients is also comparable. We use a specification of the random effects panel tobit model, which allows to relax the assumption of uncorrelatedness between the controls and error term. In particular, we follow Wooldridge (2010) who suggests add the within-firm means of all time-variant controls variables into the regression and test the joint significance of those means. We also report the results in column three of Table 2. The overall test of joint significance of all means, including mean of sale shock, credit constraint, interaction term, price cost margin and firm age, at the bottom of the table suggests that these means are indeed jointly significant so that the model in column three should be the preferred one.

In the fourth column, we report results that account for the potential persistence of R&D intensity by investigating the dynamic panel tobit model which includes a lagged dependent variable. As what we would expect, R&D intensity in last year is strongly correlated to the current R&D intensity. The results are, however, robust to the change from static to dynamic model. In the same way, we perform the test of joint significance of the within means. Now, we obtain a smaller value for the overall F-test.

Finally, in the last column, we show the results from a system GMM estimation (Arellano and Bond 1991). This model allows us to examine dynamic effect and controls for endogenous variables by their own lagged terms as instruments. However, solving the problem comes with cost, that is the drastic reduction of the number of our observations. Since if we perform system GMM with R&D intensity as dependent variable, we lose too many observations to be able to get credible results. We come up with an compromise solution, that is we use total innovation expenditure as dependent variable for the GMM models. Total innovation expenditure is broader defined and includes expenditure on both tangible assets, like equipment maintenance in addition to R&D expenditure. The post-estimation statistics reveal auto-correlation of order one. With only AR(1), we can use $y_{i,t-2}$ as our first instrument and so on back to $y_{i,1}$. Our specification also passes the Sargan-test, although, as suggested by (Roodman 2009), the test should be interpreted with care in this setting.

Column five shows that the hypotheses are empirically supported also by the dynamic panel method. All sales shock, both contemporaneous and previous ones, are negative and statistically significant, which suggests that the counter-cyclical effect persists over time. All interactions terms are positive and significant,which indicates that the weakening effect of credit constraint remains over time. More interestingly, the magnitude of the effect mentioned above is quite constant and does not fade away over time. As to internal savings, only current price cost margin increases firms' incentive to engage in R&D activities, while the effect of previous is rather negligible.

In the next step, we examine the effect of subsidies and firm size on the observed results.

For this purpose, we split the full sample into two sub-samples, namely SMEs and large firms. Next, we split the sample into subsidized and non-subsidized, and finally distinguish between subsidized and non-subsidized SMEs. We perform fixed effects regression with each sub-sample and compare the coefficients. See Table 3 for the results from that exercise. The results show that large and subsidized firms have quite stable R&D investments. It does not even have the counter-cyclical effect predicted by the model, nor is it influenced by the credit constraint. Together with our descriptive statistics, the latter is understandable and, to some extent, complies with our prediction. The violation of the first hypothesis is somewhat confusing at first glance. One explanation is, opportunity cost plays a minor role in the R&D decision inside those capital-excess firms. Rather than taking fully use of the low opportunity cost during recession, their main goal is to stabilize the income flow and avoid being trapped in the financial distress.

In contrast, for SMEs and non-subsidized counterparts, both show the counter-cyclicality and the pro-cyclical effect of the credit constraint. Thus, we find that

1. The counter-cyclical effect: This effect is essentially not driven by size, but by whether

they get some subsidy or not. As we can see, not all SMEs counter-cyclically adjust their R&D investment. SMEs with subsidy act more like large firms in the sense that their R&D input is quite stable along the business cycle.

2. The effect of credit constraint: In both sub-samples SMEs and non-subsidized SMEs, we observe the pro-cyclical effect of credit constraint. However, the effect is statistically and quantitatively stronger in the non-subsidized group than in the other, which is also predicted by our model.

3. Dependence on internal financing: We find some evidence that firms depend on internal reserves for their R&D and that the presence of subsidies does not seem to affect that sensitivity strongly. This may be due to the fact, that subsidy grants are usually matched grants which means that only part of the project costs are covered by the agency and the firm needs to finance the rest.

Finally, it is important to point out that, we do observe the possibility of turning from count-cyclical into pro-cyclical, which partially differentiates our results from those of Aghion et al (2012) based on French data, where credit constraint, at most, weakens the counter-cyclical effect, but never overturns it. This may indicate that in Germany, credit constraint has a more severe consequence. When exposed to really bad credit constraint, they behave according to the cycle. While in France firms can benefit from R&D tax credits, this form of indirect R&D subsidy is absent in Germany.

Table 3: Results of Regressions on Sub-Samples

Variables	SME (1)	Large-firms (2)	Subsidized (3)	Non-subsidized (4)	SME & Non-subsidized (5)	SME & Subsidized (6)
$\Delta Sales$	-0.17**	-0.25	-0.1	-0.158**	-0.196**	-0.183
	(0.07)	(0.072)	(0.064)	(0.068)	(0.081)	(0.12)
$CreditConstraint$	-0.0002	-0.0002	-2.06 e-06	-0.0003	-0.0004*	0.0001
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0006)
$\triangle Sales * CreditConstraint$	0.0008***	6.05 e-06	0.0003	0.0008***	0.0009***	0.0007*
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
PCM	0.001*	0.026**	0.12**	0.0013**	0.0012	0.18*
	(0.006)	(0.013)	(0.048)	(0.0005)	(0.0007)	(0.09)
$Constant$	0.31***	0.21***	0.54***	0.26***	0.211**	0.55***
	(0.08)	(0.062)	(0.12)	(0.06)	(0.086)	(0.17)
Overall significance	4.26***	4.08***	3.4***	12.31***	17.07***	
Joint significance of time	11.46***	4.17**	3.66***	5.14***	3.88***	6.51***
Number of obs	2,888	2,172	1,361	3,608	2,059	746

Notes: ***,** ,* indicate a significance level of 1%, 5%, 10%. The models include a constant and 29 industry dummies. Robust standard errors in parentheses

3.4 Two natural experiments: EU enlargement and economic crisis

The previous analysis may raise concerns regarding the endogeneity of the sales shock. Further, we did not explicitly distinguish positive sales shocks from "less negative" ones. In the following, we therefore make use of two events that constituted a sales shock to certain firms. In particular, the EU enlargement in 2004 which embraced another 10 members constituted a positive shock to exporting companies because of the now much larger market. This enlargement was one of the largest single expansion with respect to territory and population removing all barriers to trade with the new member states. As can be seen in figure 3, exports increased following the enlargement, while domestic production did not. On the contrary, the 2008 global economic crisis reduced exports strongly, but did not affact domestic output. Both these events thus can be considered exogenous sales to exporting firms. Based on these considerations, we use these shocks on exporting firms as natural experiments in testing our predictions from above. We explore the effect of the different sales shocks on exporting companies, distinguishing credit constrained from non-credit constrained firms using the binary indicator as described before. Given the nature of these aggregate shocks, we employ a synthetic control group method which uses the non-exporting firms for the construction of an appropriate control group.

The basic idea of this method is to construct a weighted combination of reference group's firms to resemble the treatment group (exporters) before the policy shock and compare this "synthetic" group with real treatment group to identify the effect of a shock. Specifically, assume, $Y_{i,t}^N$, to be the R&D ratio for domestic firms not exposed to export sales shocks and $Y_{i,t}^E$ the R&D ratio for exporting firms. Before the shock, we would have $Y_{i,t}^D = Y_{i,t}^E$. After the shock (assume t_0 is the time export shock took place), we would expect observed outcome for treatment be

$$Y_{i,t}^E = Y_{i,t}^D + \alpha_{i,t} \tag{11}$$

where $\alpha_{i,t}$ captures the effect of export shock.

Given observed $Y_{i,t}^{E}$, in order to estimate (α_{i,t_0+1},α_{i,t_0+2}....), we have to firstly estimate $Y_{i,t}^{D}$. We use the code by Abadie et al. (2010) for estimation.

The estimated external shock is then calculated based on observed outcome and the optimal weight vector

$$\hat{\alpha_{1,t}} = Y_{1,t} - \sum_{j=2}^{J+1} w_j Y_{j,t} \tag{12}$$

From Table 7, we see that the prediction power for our "synthetic" group is satisfactory showing no differences in the control variables between the groups.

We stick to the previous specifications and control variables. Since this method requires strongly balanced panel data, we impute missing value for the continuous control variables with the sector and size-class mean of those variables. The results are depicted in figure 1. The upper panel shows the positive demand shock effect in 2004 and the lower panel the 2008 crisis effect. The graphs on the left show the results for the non-credit constrained firms and the right hand side the ones for the credit constrained sub-sample.

For the non-credit constrained firms, we basically find results in line with our previous ones. That is during boom in 2004, they reduced their R&D investment for pursuit of higher current profit through capital investments. For the constrained firms, we find a similar counter-cyclical pattern which suggests that credit constraints have no effect in booms (compare left and right in upper panel of figure1). Looking at the negative shock to exporters in 2008, we see that while non-constrained firms hardly changed their R&D-intensity in response to the crisis, credit constrained exporters reduced their R&D. This is in line with our previous prediction that credit constraints turn firms' R&D more pro-cyclical.

Finally, it is worth mentioning that in response to the 2004 enlargement, the non-exporting control group indeed behaved as expected (no reaction to the shock), after 2008, however, the shock seemed to have translated into domestic firms. In particular, we see that the non-constrained control behaved counter-cyclical and the constrained control group pro-cyclical. The reason for this might be overall higher levels of uncertainty and banks reluctant to lend which negatively affected R&D also of non-exporters whose sales should not have suffered as much from the crisis as those of exporters.

4 Discussion and conclusion

The paper examines the cyclical R&D investment in the presence of credit constraints and R&D subsidies. We complement current literature, both theoretically and empirically.

Firstly, we set up a simple theoretical model through which we argue that it is efficient for the firm to invest R&D counter-cyclically. Nevertheless, this counter-cyclical pattern can be weakened by the presence of credit constraints, while subsidies have the countervailing effect. Secondly, results from empirical analysis based on firm-level data for Germany show that without credit constraint, R&D investments indeed tend to be counter-cyclical. For large or subsidized firms, investment behaves quite stable and only depends on internal funding. In SMEs or non-subsidized firms, we do observe the pro-cyclical effect of credit constraints. In non-subsidized SMEs, the effect of the credit constraint is the strongest. In addition, we studied two natural experiments, the EU enlargement in 2004 and the economic crisis in 2008, to test the effects of exogenous sales shock on R&D. While the former constituted a positive sales shock to exporters, the latter was clearly related to a negative one. Employing a synthetic control group method (Abadie and Gardeazabal 2003, Abadie et al. 2010) and using weighted averages from non-exporting firms as control group, we found that among exporting firms the effect of credit constraints on pro-cyclicality only holds for the negative shock of 2008, while R&D investments decrease during period of sales booms. These results are interesting for innovation policy. The results support a smoothing effect of R&D subsidies avoiding firms to cut back R&D in recessions. Targeting these subsidy schemes at SMEs may be most effective since larger firms are not as sensitive to movements in demand either because of higher reserves or better access to financing. The access to more detailed and more accurate data (credit constraints) and the particular policy environment in Germany (only direct grant) allows us to go one step further in exploring how firm heterogeneity plays a role in shaping the relationship between R&D investment and the business cycle.

We encourage future research addressing

1. How exporting firms compare to locally active firms given the potential trade-off between positive effects from having sales dispersion and extra cost from entering foreign markets and being expose to internal competition.

2. Further, motivated by insignificant relationship between business cycle and R&D investment (Saint-Paul 1993), it might be interesting to split the aggregate R&D into expenditure on Research(R) and Development(D) and perform the empirical investigation on both types. Research activities being more intangible in nature may be more sensitive to cash-shortages and more costly to finance externally.

Figure 1: 2004 VS 2008 & Non-Credit Constrained VS Credit Constrained

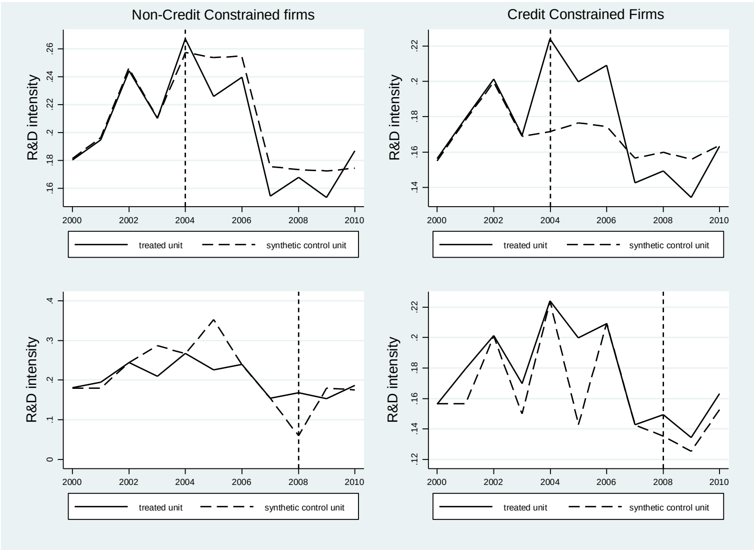

Figure 2: Growth Rate of GDP and R&D Investment

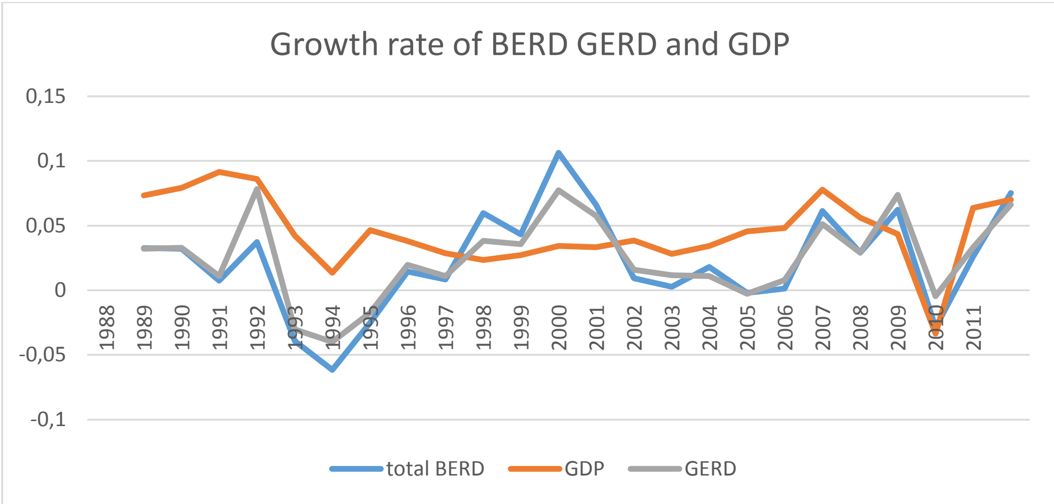

Figure 3: Growth rate of GDP: Domestic GDP versus Export GDP

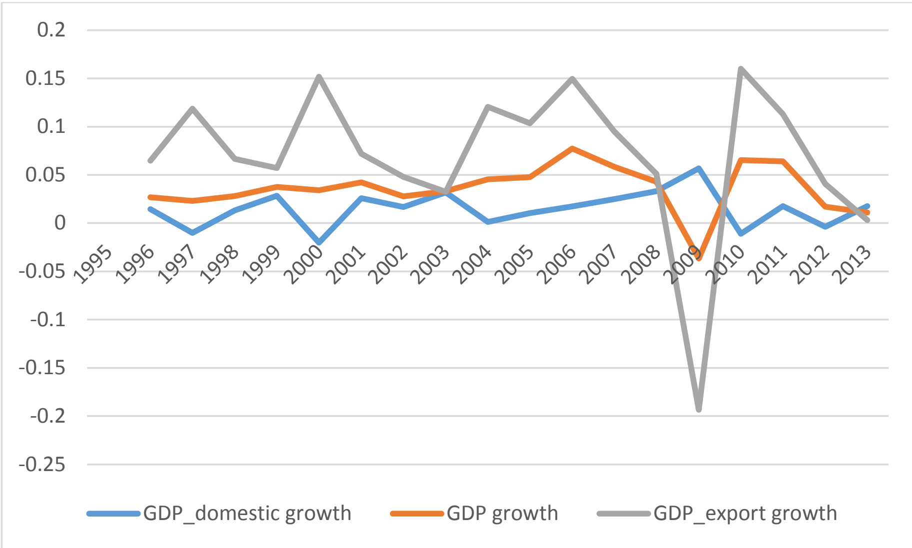

Table 4: Industry Classification

Industry	NACE rev. 2008	Description	Number of firms	Percentage
1	1.1; 1.2; 1.4; 2; 3;	Agriculture/Forestry/Fishing	7	0.13
2	6-9;	Mining	59	1.1
3	11; 12;	Food/tobacco	168	3.13
4	13; 14; 15;	Textiles	167	3.11
5	16,17	Paper/wood	199	3.71
6	18	print	145	2.7
7	19	Coke/oil	39	0.73
8	20	Chemicals	271	5.05
9	21	Pharmacy	48	0.89
10	22,23	Plastics/Rubber/Non-metal	499	9.3
11	24	Basic Metal	147	2.74
12	25	Fabricated metal	380	7.08
13	26	Computers/Electronics	425	7.92
14	27	Electronic equipment	406	7.57
15	28	Machinery nec	667	12.43
16	29,3	Vehicles	79	1.47
17	31	Furniture	98	1.83
18	32	Other manufacturing	60	1.12
19	33,34	Repair of machinery s	140	2.61
20	35	Electricity/ Gas	116	2.16
21	36-40	Water/waste	37	0.69
22	41-43	Construction	95	1.77
23	45-47	Wholesale/Retail	134	2.5
24	49-55	Transport/Communication	123	2.29
25	59-63	Information/ Communication	227	4.23
26	64.3-69	Bank/Institutions/Real-state	145	2.7
27	70; 71; 72; 73.1-74.3; 75;	Prof/ Scientific/Tech-Services	343	6.39
28	74.9; 78-82	Admin/ Support services	50	0.93
29	77; 84-88; 90-99	Social/ Other services	90	1.68
Total			5,364	100

Table 5: Cross-Correlation Matrix

	$R\&Dintensity$	$\triangle Sale$	$CreditConstraint$	$\triangle Sale * CreditConstraint$	$Subsidy$	PCM	sme
$R\&Dintensity$	1						
$\triangle Sale$	-0.0012	1					
$CreditConstraint$	0.053*	-0.042*	1				
$\triangle Sale * CreditConstraint$	0.0053	0.964*	-0.0518*	1			
$Subsidy$	0.263*	0.0298	-0.008	0.0212	1		
PCM	0.0037	-0.0253	-0.0233*	-0.03	0.0166	1	
sme	0.073*	-0.075*	0.3758*	-0.0587*	-0.0213*	0.003	1

Note: * indicates a significance level of 1%.

Table 6: Comparison between our result with Dichotomy Credit Constraint setting and Aghion et al. (2012) result with Payment Incident

Variables	Credit constraint as a dummy FE	Result from Aghion IVFE
$\Delta Sale$	-0.012	-0.018***
	(0.012)	(0.003)
$CreditConstraint$	0.012	0.003
	(0.024)	(0.002)
$\Delta Sale * CreditConstraint$	0.041*	0.029***
	(0.0224)	(0.01)
PCM	0.0017	
	(0.0017)	
$Constant$	0.157	
	(0.243)	
Overall significance	3.32***	
Joint significance of time	6.9***	
Joint significance of industry	1.32	
Number of obs	5,126	73,237

Note: the credit rating of a firm is higher than that of the 75th percentile, we set the value of credit constraint dummy to unity. Otherwise, it is zero.

Table 7: Comparison of Real, Synthetic and Mean Value of Treatment Group

Variables	Non-Credit Constrained Exporters in 2004		Average of non-Credit Constrained exporters
	Real	Synthetic	
$CreditConstraint$	211.9	218.8	195.2
PCM	-0.14	-0.39	0.27
$ln(FirmAge)$	3.24	3.37	3.44
$Capitalintensity$	0.08	0.21	0.27
$R\&Dintensity$	0.21	0.21	0.06
	Credit Constrained Exporters in 2004		Average of Credit Constrained Non-exporters
	Real	Synthetic	
$CreditConstraint$	199.9	244.45	268.32
PCM	0.284	-0.54	-0.03
$ln(FirmAge)$	3.35	3.21	3.06
$Capitalintensity$	0.127	0.132	0.16
$R\&Dintensity$	0.17	0.17	0.07
	Non-Credit Constrained Exporters in 2008		Average of Non-Credit Contrained Non-Exporters
	Real	Synthetic	
$CreditConstraint$	221.9	219	195.2
PCM	0.26	0.26	0.27
$ln(FirmAge)$	3.35	3.31	3.44
$Capitalintensity$	0.1	0.098	0.27
$R\&Dintensity$	0.155	0.154	0.06
	Credit Constrained Exporters in 2008		Average of Credit Constrained Non-exporters
	Real	Synthetic	
$CreditConstraint$	207.5	217.86	268.32
PCM	0.26	0.256	-0.03
$ln(FirmAge)$	3.4	3.37	3.06
$Capitalintensity$	0.145	0.104	0.16
$R\&Dintensity$	0.143	0.143	0.07

References

Abadie, A., A. Diamond, and J. Hainmueller, 2010. Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association* 105(490), 493–505.

Abadie, A. and J. Gardeazabal, 2003. The Economic Costs of Conflict: A Case Study of the Basque Country. *The American Economic Review* 93(1), pp. 113–132.

Aghion, P., P. Askenazy, N. Berman, G. Cette, and L. Eymard, 2012. Credit Constraints and the Cyclicality of R&D Investment: Evidence from France. *Journal of the European Economic Association* 10(5), 1001–1024.

Aghion, P. and G. Saint-Paul, 9 1998. Virtues Of bad Times Interaction Between Productivity Growth and Economic Fluctuations. *Macroeconomic Dynamics* 2, 322–344.

Arellano, M. and S. Bond, 1991. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies* 58(2), 277–297.

Barlevy, G., 2007. On the Cyclicality of Research and Development. *The American Economic Review* 97(4), 1131–1164.

Bloom, N., 2007. Uncertainty and the Dynamics of R&D. *American Economic Review* 97(2), 250–255.

Czarnitzki, D. and H. Hottenrott, 2011a. Financial Constraints: Routine Versus Cutting Edge R&D Investment. *Journal of Economics & Management Strategy* 20(1), 121–157.

Czarnitzki, D. and H. Hottenrott, 2011b. R&D investment and Financing Constraints of Small and Medium-sized Firms. *Small Business Economics* 36(1), 65–83.

Domadenik, P., J. Prasnikar, and J. Svejnar, 2008. How to Increase R&D in Transition Economies? Evidence from Slovenia. *Review of Development Economics* 12(1), 193–208.

Gali, J. and J. Hammour, 1992. Long-run Effects of Business Cycles. *Discussion Papers from Columbia University Department of Economics* .

Geroski, P., 1994. *Market Structure, Corporate Performance, and Innovative Activity*, Oxford.

Gertler, M. and S. Gilchrist, May 1994. Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms. *The Quarterly Journal of Economics* 109(2), 309–340.

Hall, B. H., 1992. Investment and Research and Development at the Firm level: Does the Source of Financing Matter?. *NBER Working Paper No.4096* 1.

Himmelberg, C. P. and B. C. Petersen, 1994. R & D and Internal Finance: A Panel Study of Small Firms in High-Tech Industries. *The Review of Economics and Statistics* 76(1), pp. 38–51.

Lopez-Garcia, P., J. M. Montero, and E. Moral-Benito, 2012. Business Cycles and Investment in Intangibles: Evidence from Spanish Firms. *Banco de Espana Working Paper No. 1219* 1, 1–42.

Rafferty, M. C., 2003. Do Business Cycles Influence Long-run Growth? The Effect of Aggregate Demand on Firm-financed R&D Expenditures. *Eastern Economic Journal* 29(4), 607–618.

Roodman, D., 2009. How to do xtabond2: An Introduction to Difference and System GMM in Stata. *Stata Journal* 9(1), 86–136(51).

Saint-Paul, G., 1993. Productivity Growth and the Structure of the Business Cycle. *European Economic Review* 37(4), 861 – 883.

Sharpe, S. A., 1994. Financial Market Imperfections, Firm Leverage, and the Cyclicality of Employment. *The American Economic Review* 84(4), 1060–1074.

Waelde, K. and U. Woitek, 2004. R&D Expenditure in G7 Countries and the Implications for Endogenous Fluctuations and Growth. *Economics Letters* 82(1), 91–97.

Wooldridge, J. M., 2010. *Econometric analysis of cross section and panel data*.