# R&D SMOOTHING: REVISITING THE CONSENSUS ON THE CYCLICALITY OF RESEARCH SPENDING

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Abstract. Using industry and firm level data on research spending and value added, I revisit the debate over the cyclical pattern of R&D and its implications for Schumpeter's opportunity cost hypothesis. The results overwhelmingly suggest that there is a significant degree of smoothing in research spending, which implies both pro-cyclical behaviour in its growth rate as well as counter-cyclical behaviour in the share of R&D on output. Evidence in favour of modified version of the opportunity cost hypothesis is also uncovered, with firms investing counter-cyclically in research as measured by its ratio with respect to the sum of R&D and capital expenditures. Established theories for the observed pro-cyclical behaviour are formally tested, with those based on the demand-pull idea receiving significantly more empirical support than alternatives such as internal and/or external financial constraints.

**Keywords**: research & development, endogenous growth, cycles.

**JEL Classification**: E22, E32, O16, O30, O32

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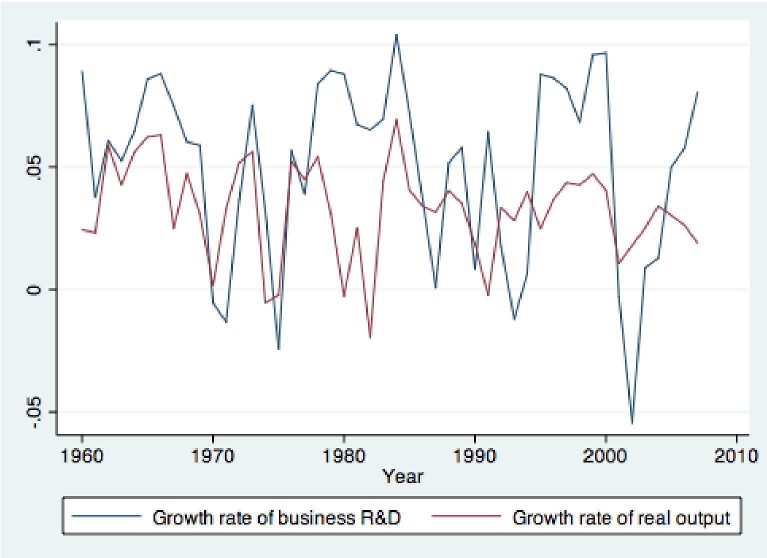
## 1. Introduction

In *Capitalism, Socialism and Democracy*, Schumpeter (1939) outlined an important argument for a potentially beneficial consequence of periods of decreased economic activity, the idea that firms respond to reduced demand for their products by investing in new processes, products and services that will accrue higher profits during the recovery phase. In other words, recessions have a *cleansing* effect, in that they not only force inefficient concerns out of businesses, but they provide the necessary incentives for outdated products, processes or services to be phased out and replaced by more efficient ones, thereby contributing towards the process of technological progress.

However intuitive the notion, attempts to demonstrate this effect empirically have concluded that spending in research and development largely shadows fluctuations in spending or output, which directly contradicts the initial hypothesis. A cursory look at US aggregate data for the period between 1960 and 2008 supports this view:

Figure 1. Growth rate of business R&D and RGDP

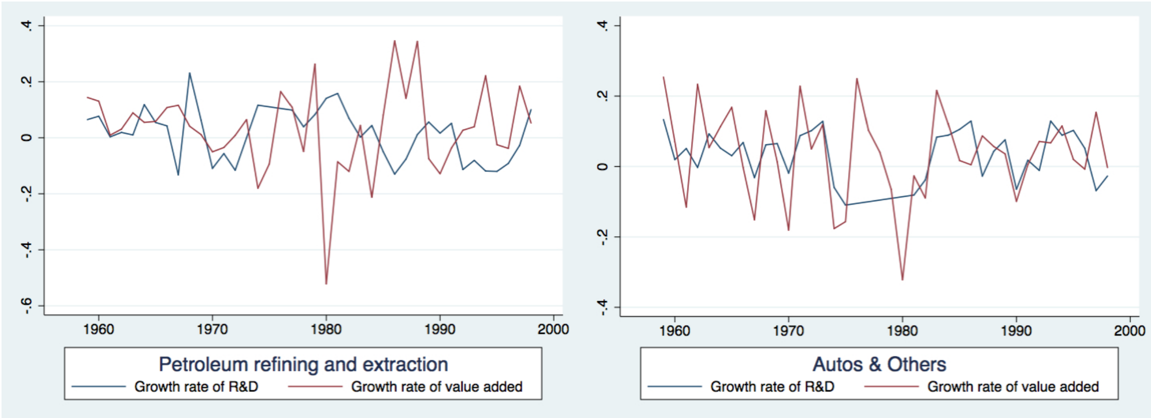



Although the correlation between the two is not perfect, a statistically significant correlation of 0.37 indicates, at the very least, that if there is a counter-cyclical relationship at the firm level, it does not extend to aggregate variables[1]. Asking the same question of US data at the industry level paints a much murkier picture, with R&D in some of them

[1] The same exercise using a HP filter on the data instead of growth rates yields identical results.

displaying a counter-cyclical profile (such as Petroleum, with a correlation of -0.31) and others a strongly pro-cyclical one (like Autos & Others, with a correlation of 0.50):

FIGURE 2. Growth rate of industry R&D and Value Added




The lack of a straightforward answer warrants closer inspection and a systematised approach to try and provide a clearer picture of the behaviour of research expenditure over the business cycle. In this paper, I propose just such an exercise by looking at the relationship between research spending and the cycle at the industry level using data lifted from the NSF and the NBER manufacturing productivity database, and at the firm level using Compustat data and data from the NIPA-BEA tables.

Throughout, I will seek to reconcile seemingly mixed evidence on the cyclical pattern of aggregate research spending by repurposing the concept of R&D smoothing proposed in Brown and Petersen (2011) to argue that at most levels of aggregation, research spending responds less than proportionately to fluctuations in output. I use three different types of measure of its cyclicality and argue that they can all be explained by making use of this concept, as well as tying together conflicting findings in the literature. The first type is measure is the elasticity of research spending with respect to output, captured by the partial correlation of its growth rate with the growth rate of output, which is proxied by gross output, value added and sales. A second type of measure is the partial correlation of the growth rate of research spending with the ratio of R&D to output, again measured using gross output, value added and sales. Finally, the third measure is the partial correlation between research expenditure and the ratio of R&D to total investment, defined as the sum between investment in research and physical capital.

If the hypothesis of R&D smoothing is correct, the observed elasticity must be positive but not exceed one, while the correlation of spending and both ratios must be negative. This implies that research spending will be pro-cyclical if measured using the first type and counter-cyclical using the other two, which suggests that much of the apparent tension between results proposed by earlier authors can be resolved under this unifying framework. Finally, I also argue, by appealing to the use of synthetic financial constraint indexes common in the finance literature, that these do not suggest that the pro-cyclical behaviour of research expenditure is driven by these constraints.

## 2. Literature Review

The fundamental idea behind the argument for the counter-cyclicality of resources devoted to innovative activity is that companies ought to find it optimal to shift resources to it during periods of decreased demand for their output. If sales of goods and services fall during a downturn, then the opportunity cost of diverting real resources to research budgets decreases and, therefore, firms should find it optimal to devote less resources to their respective productive processes and instead try to devise improvements to them or the finished good or service. This, in turn, should imply a negative relationship between the rates of change of research spending and sales or output along the cycle.

As previously mentioned, the empirical support for this theoretical prediction is, at best, scarce. A useful starting point in this discussion is Kleinknecht and Verspagen (1990), who revisit and restate the seminal contribution of a 'demand-pull' theory of inventive activity proposed by Schmookler (1966). This is sharp contrast with the Schumpeterian narrative. Under this view, the resources diverted to innovative activity are generated internally through the companies' earnings and profits, which implies that if this is a sufficiently important driver of the process of optimally allocating resources to research spending, then we ought to expect it to display a strongly pro-cyclical, rather than counter-cyclical behaviour. The aforementioned evidence in Kleinknecht and Verspagen (1990), partly corroborates that view. Scherer (1982), in a similar exercise to the previously mentioned authors further lends support to that view. Finally, that too is the case in Bosworth and Westaway (1984), who find evidence for research activity to respond along with cyclical fluctuations in firm profits, thus strengthening the argument towards the 'demand-pull' with internal financing model for spending in inventive activity[2].

Geroski and Walters (1995) address the question of the cyclicality of R&D directly by looking at the relationship between it and fluctuations in output directly. Their work concludes that apart from an expected long run relationship between economic activity and innovative activity, variations in research expenditure can be said to be Granger caused by fluctuations in output. A similar approach with firm and industry level data is proposed in Rafferty and Funk (2004). They use an error correction model to examine both the long-run and short-run relationships between output and innovative activity, and conclude that there is no evidence in favour of the opportunity cost hypothesis, i.e., R&D expenditure is pro-cyclical with respect to growth in firm sales while their proxy for "demand" shows counter-cyclical (but statistically insignificant) behaviour. It is worth noting that the authors use the deflated value of shipments for the industry as a "cleaner" measure for demand for the product[3], but it is possible that, in the presence of industry wide productivity shocks, this measure falls some way short of being a clean measure of fluctuations in demand.

Wälde and Woitek (2004) look at the correlation coefficients between the deviations of per capita R&D and GDP from a fitted trend and confirm the porous consensus that research expenditure, especially at the aggregate level, is more likely than not to display pro-cyclical behaviour. Saint-Paul (1993), examining the effect of demand innovations R&D expenditures through a VAR approach, finds that "there remains very little evidence of any pro- or counter-cyclical behavior of R&D once one tries to distinguish between demand and supply shocks".

Using data on 20 manufacturing industries, Ouyang (2011), examines possible causes for the pro-cyclical behaviour of R&D and argues that liquidity constraints might be an important channel through which demand side fluctuations contribute to the pro-cyclicality of research spending. That would imply that although R&D is pro-cyclical in the data, that pattern might be present only because liquidity constraints prevent firms

[2]Evidence for the internal financing channel in high-tech industries is discussed in Himmelberg and Petersen (1994).

[3]The implication here is that relying on firm level variables like sales or value added captures supply as well as demand, and that makes sales an unreliable measure of fluctuations in output that are not driven by productivity changes.

from taking advantage of the reduced opportunity cost of engaging in research activity. The absence of a direct measure of liquidity constraints does mean we should be cautious in interpreting the results, but it does seem to strongly indicate an asymmetry in the response of R&D efforts to changes in output. Barlevy (2007), again finds evidence of pro-cyclical research spending at the firm level, but the presence of credit constraints, to the extent that they affect balance sheet variables, does not seem to reduce the degree of its pro-cyclical behaviour.

The evidence is far murkier than the previously discussed evidence would seem to suggest, however. Indeed, Aghion et al. (2012), report counter-cyclical investment in R&D (though not statistically significant) even without including their measure of financial constraints for French firm level data. That negative relationship is highly significant when doing so, and overall their measure of R&D spending responds pro-cyclically to changes in sales growth if financial constraints are considered. Additional work by Bovha-Padilla et al. (2009) for Slovenian firm data find evidence that further corroborates Aghion et al. (2012) in their conclusion that there is some evidence for the opportunity cost hypothesis.

A final piece to the puzzle is the work by Männasoo and Meriküll (2011), who, using micro-data from a survey by the World Bank/EBRD of a variety of European countries, find that financial constraints do significantly impact on a firm's ability to engage in R&D spending[4]. Additionally, they find that even taking those constraints into account, whether a firm engages in R&D or not responds positively to changes in sales, and negatively, as well as asymmetrically, to changes in demand[5]. These results should be interpreted with a degree of caution, given that the dependent variable is the probability of doing research. Given that changes to the amounts devoted to investment in innovation are not measured, the results give us far more information about the firm-industry characteristics that are likely to be good predictors of whether any given firm is likely to devote resources to R&D.

[4]This would mean that although firms may significantly rely in the internal channel for the financing of research spending, they are constrained in their ability to resort to outside financing. In turn, this would likely prevent them from expanding that category of spending should they so desire during periods of reduced economic activity.

[5]The authors use industry output as a proxy for demand, just as in Rafferty and Funk (2004).

## 3. Modelling approach

The evidence presented in the preceding section allows us to establish some empirical regularities about the cyclical profile of research spending, which I will refer to as quasi-stylised facts[6]. The first of these is that correlations between the rates of change[7] of spending in research and a variable measuring firm output[8] are usually positive and statistically significant. This is an important starting point because any explanatory theory must satisfactorily address this recurring statistical pattern. The second quasi-stylised fact concerns the role of liquidity or financial constraints: though they are not always directly observed, whenever included they contribute quite substantially towards making R&D move more in tandem with the cycle. This implies that although they may not be the only cause, they contribute towards a more pro-cyclical pattern in innovative activity than would otherwise be observed.

A third quasi-stylised fact concerns the asymmetric response of fluctuations in innovative activity to changes in output: in downturns, research spending is more strongly pro-cyclical than during expansions, during which it may even display counter-cyclical features. In conjunction with the second of these quasi-stylised facts, it provides additional weight to the argument that although firms would want to engage in more R&D in downturns, they are constrained both by their internal financing mechanisms (lower demand, lower output, lower profits) and external finance (tightening of constraints during periods of decreased economic activity). A forth and more obscure quasi-stylised fact concerns the difference in the sign of the correlation when using different measures of the R&D response to fluctuations in output. Specifically, whenever the change, deviation or growth rate in research spending is used as the dependent variable, it behaves pro-cyclically. That is to say, the partial correlation between the growth rate of R&D and the growth rate of output is usually positive, even after controlling for other sources of variation[9]. On the other hand, when the variable used is the ratio of research spending to output, sales

[6]This choice of terminology is due to the fact that I mostly refer to results common in the literature over which there is a significant degree of disagreement. This paper proposes to tie these in a unifying framework, but it would be abusive to refer to them as stylised facts.

[7]As measured by the growth rate or deviations from a trend calculated using a filter like Hodrick-Prescott.

[8]Gross output, value added or net sales/revenue are the most common.

[9]The caveats identified in the second and third points do apply here, however.

or even total investment, its response to fluctuations in output is counter-cyclical at a statistically significant level when other control variables are included.

These quasi-stylised facts, with particular emphasis to the last one, suggest that research spending is 'smoothed' by companies across the cycle, with the response elasticity of R&D to fluctuations in output not exceeding unity. Consequently, when cyclical fluctuations are measured as the ratio of research expenditure to a proxy of output, the implication is that this ratio should display counter-cyclical features. Additionally, I argue that this smoothing behaviour extends to firms' decisions to invest in capital purchases or research spending. By defining total investment as the sum of capital and research expenditures, I argue that smoothing implies that the ratio of R&D expenses to this variable should behave counter-cyclically because firms are much more willing to allow their capital expenditure to fluctuate. The R&D smoothing hypothesis suggests that the opportunity cost hypothesis - if the various strands of evidence, as well as the static-dynamic trade-off that the original contribution by Schumpeter ignored, are taken into consideration - is only partially correct. Spending follows the cycle but firms respond to the pro-cyclical opportunity cost by attempting to smooth out the effects of output fluctuations on research and development expenditures.

Competing explanations such as liquidity constrains or asymmetric responses are taken into account and incorporated into the central thesis of this paper, rather than proposed as alternative mechanisms driving the observed pro-cyclicality of research spending. By looking at the response of the three types of measures proposed at the beginning of this section according to different degrees of likelihood of experiencing financial constraints, their direct impact on any of these three is then made clear.

3.1. **Structure, data and benchmark models.** This contribution seeks to examine all four of the quasi-stylised facts highlighted in the previous section by combining data from four different sources: the BEA/NIPA industrial output, disaggregated NSF data on research spending by industry, the NBER Manufacturing Productivity database by Bartelsman et al. (1996), and Compustat firm level data.

The first dataset is the result of combining 20 manufacturing industries for which the NSF provides disaggregated R&D expenditure with data for value added from the NBER Manufacturing Productivity database. Following the approach in Ouyang (2011), we begin by analysing the correlation between the growth rate in company reported R&D

and the growth rate of value added, and the growth rate of the value of shipments. A dummy variable will be included to account for the asymmetric response of research spending to fluctuations in output and, in order to deal with the issue of both output and research spending being co-determined, value added and shipment value are instrumented by aggregate output. Given the incompleteness of the company data, all versions of the model are run on three different measures of R&D growth: the raw data, a series where gaps have been filled by multiple imputation, and a series wherein gaps are filled with recourse to linear interpolation. Details of these procedures can be found in the appendix, as well as summary statistics and other information on the dataset. We can then summarise the first model to be estimated as follows:

$$\Delta \ln rd_{i,t} = \beta_0 + \beta_1 \Delta \ln y_{i,t} + \boldsymbol{\lambda X_{i,t}} + \boldsymbol{\gamma \tau_t} + \delta_i + \epsilon_{i,t} \tag{1}$$

Where $\boldsymbol{\tau_t}$ is a vector of time fixed effects, $\delta_i$ a variable capturing firm fixed effects and $\boldsymbol{X_{i,t}}$ a vector of controls that include industry size (measured by the number of employees), and the total book value of physical capital. Two variants of this equation are also estimated, with the ratio of R&D expenditure to value added, and the ratio of research expenditure over total investment expenditure[10] as the dependent variables.

The second model to be estimated is a dynamic model for the share of R&D over the relevant output measure ($s_{i,t}$), in this case value added; which is common in the literature and generally associated with evidence of counter-cyclical behaviour. Its inclusion allows for a richer and fuller picture of the dynamics of research expenditure and provides an alternative way of looking at whether the opportunity cost hypothesis might hold in this more narrow sense.

$$s_{i,t} = \beta_0 + \beta_1 \Delta \ln y_{i,t} + \sum_{k=1}^{K} \pi_k s_{i,t-k} + \boldsymbol{\lambda X_{i,t}} + \boldsymbol{\gamma \tau_t} + \delta_i + \epsilon_{i,t} \tag{2}$$

The third model is a simple variation of equation 2, in which the dependent variable is the aforementioned ratio between research and capital expenditures, $z|i_{i,t}$. Including this third measure is justified on the grounds that the preceding two models are dependent, in the sense that if research expenditures don't grow at the same rate as output, then its ratio falls mechanically. In order to test whether the same can be said of other expenditure categories and, specifically, whether the 'opportunity cost' hypothesis is validated in some

[10] This variable is defined as: $z|i_{i,t} = \frac{rd_{i,t}}{capx_{i,t} + rd_{i,t}}$.

way, it is natural to test whether this measure of R&D intensity behaves counter-cyclically at the firm level.

$$z|i_{i,t} = \beta_0 + \beta_1 \Delta \ln y_{i,t} + \sum_{k=1}^{K} \pi_k z|i_{i,t-k} + \boldsymbol{\lambda X_{i,t}} + \boldsymbol{\gamma \tau_t} + \delta_i + \epsilon_{i,t} \tag{3}$$

A second dataset merges data from the NBER Manufacturing Productivity database on value added and value of shipments for manufacturing industries using their 4-digit SIC code, which is matched with the same code on the Compustat database. This allows me to combine detailed balance sheet information on each firm with information on the industry's level of output that can then be used as demand instruments. In contrast with Barlevy (2007), rather than estimating the relationship between fluctuations in R&D spending and the rate of change in industry output ($y_{i,t}$), I estimate the following version of equation 1:

$$\Delta \ln rd_{i,j,t} = \beta_0 + \beta_1 \Delta \ln y_{i,j,t} + \boldsymbol{\lambda X_{j,i,t}} + \boldsymbol{\gamma \tau_t} + \delta_{i,j} + \epsilon_{i,j,t}$$

The main difference between the two equations is due to the relevant variables being measured at the firm level in this instance, which also implies that the controls vector now includes a variety of balance sheet variables[11]. Two variables are used as proxies for output growth in this instance, the growth rate of a measure of value added and the growth rate of sales. Versions of equations 2 and 3 are also estimated using this data and those models are, respectively:

$$s_{i,j,t} = \beta_0 + \beta_1 \Delta \ln y_{i,j,t} + \sum_{k=1}^{K} \pi_k s_{i,j,t-k} + \boldsymbol{\lambda X_{i,j,t}} + \boldsymbol{\gamma \tau_t} + \delta_{i,j} + \epsilon_{i,j,t}$$

For the ratio of R&D to the output variable, and:

$$z|i_{i,t} = \beta_0 + \beta_1 \Delta \ln y_{i,j,t} + \sum_{k=1}^{K} \pi_k z|i_{i,t-k} + \boldsymbol{\lambda X_{i,t}} + \boldsymbol{\gamma \tau_t} + \delta_i + \epsilon_{i,j,t}$$

For the ratio of R&D to total investment. A third dataset is constructed using the BEA's Annual Industry Accounts and again Compustat firm level data. From the former I build time series for value added and gross output for a number of industries and composite industries, using the 3-digit NAICS code to match them with company observations. The model to be estimated is the same as in equation (2), but instead of focusing on

[11]See appendix for details.

manufacturing firms, all firms to which Compustat assigns a NAICS code are assigned the previously mentioned 3-digit industry gross output and value added series.

3.1.1. *Asymmetric responses.* Internal constraints to investment in research are often proposed as possible reasons for why it displays a pro-cyclical bias, which would imply, if true, an asymmetrical response of R&D to changes in output depending on the phase of the cycle. In order to test for this hypothesis, the output growth series is split into two different series, one for all positive instances of output growth, and one for all negative instances of negative growth. Version of the previously discussed models are then estimated, including both of these regressors, $\Delta y^{+}_{i,j,t}$ and $\Delta y^{-}_{i,j,t}$, rather than the single series, $\Delta y_{i,j,t}$. If the hypothesis is true, we would expect a negative coefficient associated with $\Delta y^{+}_{i,j,t}$ and a positive coefficient associated with $\Delta y^{-}_{i,j,t}$.

3.1.2. *Simultaneity and robustness.* One potential concern with the estimates from the models previously outlined, as discussed in Männasoo and Meriküll (2011) and Aghion et al. (2012), is that they may be biased as the endogenous and explanatory variable may be co-determined. A well known strategy in this context is to identify covariates of the potentially endogenous regressors that would likely be uncorrelated with the error term in the main regression, and then estimate the same coefficients using a two-step least squares or generalised method of moments method to correct for this possible source of bias. Choosing the right instruments is, therefore, an important process. For the first panel of industry-wide data, I follow Männasoo and Meriküll (2011), and use the growth rate of real GDP is used as a demand side instrument for value added data at the industry level.

When dealing with firm-level data, I use the information on industry value added and value of shipments on the NBER Manufacturing Productivity database for all manufacturing industries, and value added and gross output at the industry level data available in the BEA's Annual Industry Accounts. Using aggregate data may be problematic if the aggregate instrument is correlated with the innovations on the firm side, but there is little reason to assume that is the case in this context. Demand shocks at the industry level have a significant impact on firms' decision making process, but that channel through which they do so is likely to be firms' own sales growth or value added. In other words, there is no reason to expect firms to set R&D expenditure plans on the basis of fluctuations in industry output or value added that do not affect its own output or sales. To ensure that a single firm isn't overrepresented in the sample, all regressions are restricted to include only firms whose value added accounts for less than 10% of total industry value added.

3.2. **Financial constraints.** The final dataset is the entire Compustat panel, with observations filtered out to include only firms that engage in R&D and have a stock price and number of outstanding common shares pair. The reason for the last restriction is so that two measures of financial constraints can be derived, which will, in principle, allow for an explicit test of the way the presence of these affects firms' decision to engage in R&D. Following the literature on deriving those financial constraints indexes, data for firms in the financial industries is removed as well. The model to be estimated is:

$$\Delta \ln rd_{i,j,t} = \beta_0 + \sum_{k=1}^{4} \beta_k I^k_{i,j,t} \Delta \ln y_{i,j,t} + \boldsymbol{\lambda X_{j,i,t}} + \boldsymbol{\gamma \tau_t} + \delta_{i,j} + \epsilon_{i,j,t} \tag{4}$$

Where the first independent variable is now real sales growth. An additional measure of output included in the analysis is value added[12], which is constructed using information from the firm's balance sheet variables. As in the previous models, the same equation will be estimated using as dependent variables the ratio between research spending and net sales, value added and the ratio of R&D to total investment. The variable $I_{i,j,t}$ is one of two composite variables that I use to capture firm-level financial constraints are the KZ-index (using the formula in Lamont et al. (2001)) and the WW-index, which is described in more detail in Whited and Wu (2006). As discussed in Hadlock and Pierce (2010), however, both indexes are often in direct contradiction and, additionally, may be unreliable when extrapolated from the samples which were used to estimate them. In order to ensure a greater degree of generality, I will also include three variables that capture aggregate changes in financing conditions for companies, namely spreads between commercial and government bonds[13].

3.3. **Summary.** The R&D smoothing hypothesis can then be summarised in a few hypotheses that can be tested explicitly, which I have divided into four broad categories and are outlined as follows:

[12]Definition in the appendix.

[13]Full description in the appendix.

- R&D displays pro-cyclical behaviour when measured by the response of the growth rate or deviation from trend of research spending to changes in the growth rate or deviation from trend of a measure of output. This is consistent with the 'demand-pull' hypothesis proposed by Schmookler (1966), and as described in Kleinknecht and Verspagen (1990);
- R&D displays counter-cyclical behaviour when measured by the response of the ratio of research spending to output / ratio of research spending to the sum of capital expenditure and research spending (total investment) to changes in the growth rate or deviation from trend of a measure of output. This is partly consistent with Schumpeter's 'opportunity cost' hypothesis;
- The response of any one of the aforementioned measures should respond asymmetrically to changes in the growth rate or deviation from trend of a measure of output depending on whether the latter is positive or negative. Evidence for this would support the idea that R&D would be even more counter-cyclical were it not constrained by output demand through constraints to firms' ability to finance it through profits and earnings;
- The cyclical pattern of R&D should vary according to the ease with which firms can finance such expenditures, with more constrained firms displaying more pro-cyclical behaviour than otherwise. Alongside cross-sectional variation in firms' ability to finance investment spending, if financial constraints matter, that should also be evident when considering period specific changes to the cost of external finance, with asymmetric responses for periods when credit is cheaper relative to periods when it is dearer.

## 4. Results

In this section I will summarise the key results for each of the datasets, with the bulk of auxiliary regressions and alternative specifications, as well as their discussion, being presented at length in the annex.

4.1. **Industry Data - Manufacturing.** An exploratory analysis of the data seems to indicate a positive relationship between the growth rates of research spending and the growth rates of shipment value and value added. Looking at the results in table 1, the relationship between the growth rate of value added and the growth rate of research spending is positive and significant at the 5% level, but when estimating that relationship using fixed effects, the coefficient is no longer significant. Unlike previous research, in which Ouyang (2011), finds that this relationship is significant, I include additional controls such as plant and equipment value, as well as year fixed effects. Although the aggregate data does fail to provide strong evidence for the pro-cyclicality of research spending, it does confirm the hypothesis outlined earlier that the fraction of research spending to output behaves counter-cyclically, even when including industry fixed effects. Looking at a measure of how firms decide between research and investment spending also indicates that firms respond counter-cyclically to changes in the growth rate of value added.

Table 1: R&D ($z_{j,t}$) and Industry Value Added ($y_{j,t}$)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $\Delta \ln z_{i,t}$ | $\Delta \ln z_{i,t}$ | $s_{i,t}$ | $s_{i,t}$ | $z \mid i_{i,t}$ | $z \mid i_{i,t}$ |
| Lags | - | - | (2) | (2) | (2) | (2) |
| $\Delta \ln y_{i,t}$ | 0.144* | 0.114 | -0.0494*** | -0.0536* | -0.0817*** | -0.0909** |
| | (0.017) | (0.208) | (0.000) | (0.014) | (0.001) | (0.009) |
| Controls | Y | Y | Y | Y | Y | Y |
| FE | N | Y | N | Y | N | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| $N$ | 651 | 651 | 609 | 609 | 609 | 609 |

$p$-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

One of the theories put forward to explain the pro-cyclical nature of research spending is that firms would increase spending in R&D during downturns but are constrained by dwindling profits, which prevent firms from using internally generated funds to finance the additional spending. Should that be true, during periods of expansion, spending should then behave counter-cyclically, and growth in R&D should respond negatively to increases in added value. To test this[14], I divide the series for the growth rate for value added, for each industry, into two series: one for values in which growth is negative, and another in which growth is positive. According to this hypothesis, the coefficient on the positive

[14]This is the approach followed in Ouyang (2011).

growth series should be negative, while the coefficient on the negative series should be positive. Table 2 shows the relevant coefficients for both of these series, using the same endogenous variables and structure as in table 1. The coefficient of the growth rate of valued added on the growth rate of research spending is positive for both series, and the null of both coefficients being equal cannot be rejected at any degree of confidence, with both not significant at any standard level. Including industry fixed effects seems to introduce some difference between the coefficients but, again, the null of equality cannot be rejected.

Table 2: R&D ($z_{j,t}$) and Industry Value Added ($y_{j,t}$)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $\Delta \ln z_{i,t}$ | $\Delta \ln z_{i,t}$ | $s_{i,t}$ | $s_{i,t}$ | $z\|i_{i,t}$ | $z\|i_{i,t}$ |
| Lags | - | - | (2) | (2) | (2) | (2) |
| $\Delta \ln y_{j,t}{}^{+}$ | 0.156 | 0.165$^{*}$ | -0.0461$^{***}$ | -0.0511$^{***}$ | -0.0696$^{*}$ | -0.0883$^{*}$ |
| | (0.069) | (0.028) | (0.000) | (0.000) | (0.014) | (0.018) |
| $\Delta \ln y_{j,t}{}^{-}$ | 0.121 | 0.0204 | -0.0558$^{**}$ | -0.0582 | -0.105$^{*}$ | -0.0957 |
| | (0.275) | (0.903) | (0.009) | (0.126) | (0.019) | (0.051) |
| Controls | Y | Y | Y | Y | Y | Y |
| FE | N | Y | N | Y | N | Y |
| Year FE | Y | Y | Y | Y | Y | Y |
| $N$ | 651 | 651 | 609 | 609 | 609 | 609 |

$p$-values in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Looking at the ratio of R&D to value added, all coefficients are significant at the 1% level with and without fixed effects, with the exception of the coefficient for the response of the ratio to negative growth in added value. Additionally, firms seem to respond counter-cyclically regardless of whether there is positive or negative growth, which is equally true if we look at the ratio between R&D and the sum of research and capital expenditure. The coefficients using that ratio as the endogenous variable are all significant with the exception of its response to negative growth, although the p-value is very close to the 5% threshold. Taking stock of all the evidence presented in table 2, there does not seem to be any support for the idea that there is an asymmetric response during expansions in output relative to recessionary periods.

Table 3: R&D ($z_{j,t}$) and Industry Value Added ($y_{j,t}$) (GDP as IV)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $\Delta \ln z_{i,t}$ | $\Delta \ln z_{i,t}$ | $s_{i,t}$ | $s_{i,t}$ | $z\|i_{i,t}$ | $z\|i_{i,t}$ |
| Lags | - | - | (2) | (2) | (2) | (2) |
| $\Delta \ln y_{i,t}$ | 0.131 | 0.148 | -0.0326*** | -0.0294*** | -0.124** | -0.0688 |
| | (0.311) | (0.097) | (0.000) | (0.000) | (0.002) | (0.219) |
| Controls | Y | Y | Y | Y | Y | Y |
| FE | N | Y | N | Y | N | Y |
| Year FE | N | N | N | N | N | N |
| $N$ | 632 | 632 | 590 | 590 | 590 | 590 |

$p$-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As discussed previously, in order to correct this potential problem of simulateneity, I use a variety of different demand instruments previously explored in the literature, namely the growth rate of real GDP and the growth rate of manufacturing output for all the industries in the database. Doing so paints a somewhat different picture than the results presented in tables 1 and 2: while the response of the growth rate of R&D expenditure to output is still not significant, the ratio of research spending to sales responds in a qualitatively identical manner and is statistically significant, while the response of the ratio of spending in R&D to the sum of capital and research spending is no longer significant when including firm-specific fixed effects. Table 4 sheds some light on what drives these slightly different conclusions: it does point to a an asymmetric response to demand shocks, but the coefficients are not significant for the first two endogenous variables, with and without fixed effects, while the response of the research to total investment ratio, while statistically significant, is asymmetric but in an opposite direction to the theoretical prediction. Using aggregate output as an instrument is not without its own question marks, however, as it is likely it may be correlated with research spending directly via the productivity channel, in which case it would be entirely unsuitable as a demand instrument.

Table 4: R&D ($z_{j,t}$) and Industry Value Added ($y_{j,t}$) (GDP as IV)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $\Delta \ln z_{i,t}$ | $\Delta \ln z_{i,t}$ | $s_{i,t}$ | $s_{i,t}$ | $z\|i_{i,t}$ | $z\|i_{i,t}$ |
| Lags | - | - | (2) | (2) | (2) | (2) |
| $\Delta \ln y_{j,t}{}^{+}$ | -0.634 | -0.369 | -0.0531 | -0.0366 | 0.657 | 0.610$^{*}$ |
| | (0.378) | (0.534) | (0.098) | (0.082) | (0.051) | (0.018) |
| $\Delta \ln y_{j,t}{}^{-}$ | 1.089 | 0.818 | -0.00911 | -0.0208 | -0.991$^{**}$ | -0.868$^{*}$ |
| | (0.223) | (0.255) | (0.803) | (0.416) | (0.008) | (0.012) |
| Controls | Y | Y | Y | Y | Y | Y |
| FE | N | Y | N | Y | N | Y |
| Year FE | N | N | N | N | N | N |
| $N$ | 632 | 632 | 590 | 590 | 590 | 590 |

$p$-values in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Given the large variation in results when considering alternate specifications and potential sources of regressor endogeneity, as well the possibility that the instruments are inadequate, these results must be interpreted with some caution: industry level data gives mixed evidence with respect to the pro-cyclical behaviour of research spending when controls are included and somewhat stronger evidence of counter-cyclical behaviour of the ratios of R&D to value added and total investment. The hypothesis that there is an asymmetric behaviour of research spending consistent with firms drawing on internal financing to fund it is not corroborated by the data.

4.2. **Firm Data (Compustat) - Manufacturing.** An important caveat to the analysis carried out in the previous section is that by focusing only on manufacturing and with such a restricted number of industries - namely only those reporting high enough levels of R&D spending while simultaneously having a reasonably high number of firms -, might give us a skewed perception of what goes on at the firm level. Indeed, by abstracting from a multiplicity of firm-specific constraints, aggregating research spending levels and value added across firms might obscure precisely the kind of relationships we want to explain.

In order to circumvent that problem, I then look at firm level data on all manufacturing firms (two digit SIC codes between 20 and 39) available on the Compustat database. The reasons for restricting the dataset to these firms is twofold: it allows for a direct comparison with the analysis in the previous sections as it comprises the same industries, and, secondly, industry aggregate variables can be used as instruments for the relevant regressors to overcome the issue of their endogeneity.

Firm level data poses a somewhat different problem, in that there is no direct measurement of valued added, so in order to test the same hypothesis as in the previous section, I turn to two different measures of firm output: sales or turnover, which measures total revenue, and synthetic value added[15]. I then estimate the equivalent of the equations in tables 1 and 2 using these definitions, the results of which are presented in tables 5 and 6.

The first two of these tables looks at how research spending responds to changes in the growth rate of sales, equations labeled (1), using the three endogenous variables discussed previously: growth in R&D, the ratio of R&D to sales and the ratio of research spending to the sum of investment spending and R&D spending. These confirm the view that changes in research spending tend to track changes in output, increasing by roughly half of the increase in total sales, a result which is robust to using value added at the industry level as a demand instrument. The response of the ratio between research spending and sales, on the other hand, responds negatively, as expected, but that response is not significant at the 5% level, and much less so when value added is used as an instrument; finally, the fraction of R&D to total investment decreases as predicted - and in line with the industry level data -, and is strongly statistically significant.

As for evidence of an asymmetric response, the results are slightly mixed: there is virtually no difference between coefficients associated with positive or negative levels of the growth rate in sales, with each strongly statistically significant; while using the alternative endogenous variables discussed previously indicates negative coefficients, as theorised, which are not significant in the case of R&D over sales but are strongly significant in the case of R&D over total investment. In the case of the latter, the coefficient associated with periods of negative sales growth is roughly half that its counterpart for positive growth periods, suggesting, to an extent, a lesser degree of counter-cyclicality. Finally,

[15]Absence of key data on variables necessary to compute value added means an approximation to the amount spent on labour costs is necessary. Details in the appendix.

Table 5: R&D ($z_{i,j,t}$) and Sales ($y_{i,j,t}$)

Simple fixed effects

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y_{j,t}$ | 0.540*** | -0.0408 | -0.0880*** |
| | (0.000) | (0.065) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 22521 | 23028 | 22635 |

$p$-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Industry Value Added as IV

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y_{j,t}$ | 0.406** | -0.0156 | -0.310*** |
| | (0.004) | (0.612) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 19388 | 19780 | 19422 |

$p$-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Simple fixed effects

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y_{j,t}{}^{+}$ | 0.553*** | -0.00382 | -0.106*** |
| | (0.000) | (0.800) | (0.000) |
| $\Delta \ln y_{j,t}{}^{-}$ | 0.514*** | -0.109 | -0.0549*** |
| | (0.000) | (0.225) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 22521 | 23028 | 22635 |

$p$-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Industry Value Added as IV

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y_{j,t}{}^{+}$ | 0.845** | -0.0274 | -0.302** |
| | (0.004) | (0.499) | (0.002) |
| $\Delta \ln y_{j,t}{}^{-}$ | -0.213 | -0.00843 | -0.269* |
| | (0.517) | (0.803) | (0.012) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 19388 | 19780 | 19422 |

$p$-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

using industry value added as an instrument for sales growth, the results suffer significant changes: there is a strongly asymmetrical response of the dependent variable in equation (1) to sales growth, with positive values yielding a pro-cyclical estimate and negative ones a counter-cyclical response, which contradicts the theoretical prediction. Ratio of R&D to sales again responds counter-cyclically (with some difference in the two coefficients), but neither value is significant. Performing an endogeneity test given the available instruments suggests, however, that both should be treated as exogenous and, therefore, that estimates the non-instrumented coefficients are valid. That is not, however, the case of the response of research spending to total investment, which, given a significant difference between non-instrumented and instrumented coefficients, suggests that the former ought to be discarded. As can be gleaned from equation (3) in the last sub-table in table 5, doing so does suggests no evidence of an asymmetric response, as the null that both coefficients are equal cannot be rejected.

The results displayed in table 6 replicate the same models using value added rather than sales as the output variable. Given limitations in the data, value added cannot be measured directly using data in the dataset alone except for a fraction of all available observations, and a description of how it can be obtained is available in the annex. Though qualitatively similar, there are slight differences worth mentioning in the analysis of these results: R&D growth responds pro-cyclically to value added growth and both ratios respond counter-cyclically, though all coefficients are now significant when the main regressor is not instrumented. Again, using industry value added as an instrument does not significantly change the size of the coefficients in equations (1) and (2), nor their significance levels, but increases significantly the absolute size of the coefficient on the ratio of R&D spending to total investment, which mimics the result using sales as the regressor.

Looking at the asymmetric response to positive and negative changes to value added growth, the evidence is again mixed and inconclusive, with the coefficient on the response of R&D growth to positive growth in value added larger than the coefficient associated with periods of negative growth. Testing for whether the regressor should be instrumented, based on the set of instruments available, suggests that is only the case when looking at the ratio of R&D to total investment as the dependent variable.

4.3. **Firm Data (Compustat) - All industries.** The BEA's Annual Industry Accounts provides disaggregated, industry level data on gross value added and gross output, which allows me to investigate whether the results in the previous section hold when including non-manufacturing industries. Using the same models, it also allows for a direct comparison of non-instrumented results, as well as two additional sets of instruments in GDP and Gross Output by industry.

Table 6: R&D ($z_{i,j,t}$) and Value Added ($y_{i,j,t}$)

Simple fixed effects

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y_{j,t}$ | 0.225*** | -0.183*** | -0.0563*** |
| | (0.000) | (0.000) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 22312 | 22326 | 22428 |

$p$-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Industry Value Added as IV

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y_{j,t}$ | 0.276** | -0.153*** | -0.203*** |
| | (0.003) | (0.000) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 19231 | 19228 | 19269 |

$p$-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Simple fixed effects

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y^{+}_{j,t}$ | 0.294*** | -0.129*** | -0.0668*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^{-}_{j,t}$ | 0.134*** | -0.252*** | -0.0427*** |
| | (0.000) | (0.000) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 22312 | 22326 | 22428 |

$p$-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Industry Value Added as IV

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y^{+}_{j,t}$ | 0.704** | -0.172 | -0.205* |
| | (0.005) | (0.086) | (0.015) |
| $\Delta \ln y^{-}_{j,t}$ | -0.206 | -0.129 | -0.176* |
| | (0.387) | (0.126) | (0.025) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 19231 | 19228 | 19269 |

$p$-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Virtually all the main results are corroborated when examining the relationship between R&D and sales, as a cursory glance at table 7 shows; with no qualitative differences and an encouraging consistency in the size of the estimated parameters. Even when using value added, or industry GDP, as an instrument, most of the key finds are unchanged relative to the case when only manufacturing firms were considered. The only important departure concerns the response of the ratio of research spending to total spending, which is not only not significant at any level, but is a lot smaller in terms of its magnitude. On the other hand, using an alternative instrument, gross output, rather than industry value added, yields a result qualitatively and quantitatively identical to the one in table 5. Standard diagnostic tests for over-identifying restrictions favour using gross output as the demand-side instrument, but it is clear that this result is very sensitive to the choice of instrument[16].

A roughly identical story can be told when looking at table 8: these results confirm the interpretations put forward when table 6 was discussed, with notable exceptions to the parameters associated the dependent variables when the two ratios are considered and industry value added is used as an instrument. Again, using gross output as the instrument brings the magnitude of the coefficient to levels qualitatively identical to their non-instrumented variants, but in this instance the usual diagnostic statistics suggest industry value added is a more appropriate instrument for value added growth when looking at the ratio of research spending to value added; with the reverse case for the ratio of research spending to total investment. Taking all three results, similar bounds to the magnitude of the coefficient in the case when sales growth is the key regressor are found, which suggests some degree of robustness in stating that the data presents a very strong case for counter-cyclical behaviour in firms' response, particularly given that the coefficient is invariably negative and significant at the usual levels.

Despite the clarity in those results, interpreting the evidence on an asymmetrical response is remarkably tricky. As in tables 5 and 6, non-instrumented estimates do not suggest any difference in the response of research spending for all the growth on growth regressions, with all coefficients significant. Looking at the ratio of R&D to sales/value added, there is no clear pattern to be discerned, with all but one coefficient taking on negative values and said coefficient both small in terms of coefficient and statistical significance. Additionally, the asymmetric response in some instances favours the idea that low growth periods are "more pro-cyclical", but in others the opposite happens, which in turn suggests that there is no robust relationship that can be inferred from the data. Using

[16]Using only contemporaneous values of industry value added trivially satisfy the Hansen test for over-identifying restrictions, but this suggests that, given the set of exogenous instruments, the null that the suspected endogenous variable can be treated as an exogenous regressor is not rejected. Both results suggest a lower bound (non-instrumented regression) and an upper bound (instrumented using gross output) in terms of the magnitude of the effect. Both are statistically significant at standard levels.

Table 7: R&D ($z_{i,j,t}$) and Sales ($y_{i,j,t}$)

Simple fixed effects

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y_{j,t}$ | 0.552*** | -0.0249* | -0.0683*** |
| | (0.000) | (0.014) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 39545 | 45512 | 43928 |

$p$-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Industry Value Added as IV

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y_{j,t}$ | 0.287* | -0.0172 | -0.0882** |
| | (0.029) | (0.127) | (0.002) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 29701 | 33971 | 32760 |

$p$-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Simple fixed effects

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y^+_{j,t}$ | 0.585*** | -0.00848 | -0.0802*** |
| | (0.000) | (0.225) | (0.000) |
| $\Delta \ln y^-_{j,t}$ | 0.491*** | -0.0542 | -0.0465*** |
| | (0.000) | (0.176) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 39545 | 45512 | 43928 |

$p$-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Industry Value Added as IV

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y^+_{j,t}$ | 0.908*** | -0.00102 | -0.0425 |
| | (0.000) | (0.970) | (0.480) |
| $\Delta \ln y^-_{j,t}$ | -0.392 | -0.0495** | -0.136 |
| | (0.138) | (0.009) | (0.055) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 29701 | 33971 | 32760 |

$p$-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

different instruments does not remedy this problem in the slightest, often with opposite results being generated with no increase in their robustness to different specifications. Indeed, the only robust conclusion to be drawn from this exercise is that growth in R&D seems to be driven primarily by sales / value added growth during expansions, as can be inferred from equation (1) in the last panel for tables 5 through 8. The negative sign on

Table 8: R&D and Value Added

| Simple fixed effects | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y_{j,t}$ | 0.229*** | -0.171*** | -0.0424*** |
| | (0.000) | (0.000) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 35040 | 39344 | 38961 |

$p$-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

| Industry Value Added as IV | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y_{j,t}$ | 0.206* | -0.0836** | -0.0580** |
| | (0.023) | (0.003) | (0.004) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 29431 | 32739 | 32443 |

$p$-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

| Simple fixed effects | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y^{+}_{j,t}$ | 0.231*** | -0.180*** | -0.0428*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^{-}_{j,t}$ | 0.148* | 0.00106 | -0.0250 |
| | (0.015) | (0.883) | (0.083) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 35040 | 39344 | 38961 |

$p$-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

| Industry Value Added as IV | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y^{+}_{j,t}$ | 0.751*** | 0.0110 | -0.0309 |
| | (0.000) | (0.864) | (0.528) |
| $\Delta \ln y^{-}_{j,t}$ | -0.249 | -0.161** | -0.0813 |
| | (0.128) | (0.004) | (0.061) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 29431 | 32739 | 32443 |

$p$-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

periods of negative growth, though not significant, indicates counter-cyclical R&D during downturns, the opposite of what the hypothesis put forward would be consistent with.

Piecing together all the evidence, the third hypothesis mentioned at the end of the modelling approach / strategy section finds little support in the data, regardless of which instruments are used and considering both manufacturing and non-manufacturing industries. That is not true, however, of both the 'demand-pull' and counter-cyclical hypotheses, which fare reasonably well across a wide variety of specifications and models.

4.4. **Firm Data (Compustat) - Financial constraints.** The preceding discussion does not take into consideration how different degrees of access to credit might affect the way in which firms undertake investment or expenditure decisions. This is particularly important in R&D, given that investments in new technologies must be financed either by firm profits or external capital in the form of debt or equity injections. It follows that if firms are differently constrained in the ability to capture external investment or lending, and that the latter two are likely to vary significantly throughout the cycle, it is very likely that they could play an important role in determining the cyclical pattern of research expenditure.

Unfortunately, knowing which firms are financially constrained, and when, makes it exceedingly difficult to control for their effect on the outlays on R&D. To do so, I construct three different indicators of financial constraints: the Kaplan-Zingales Index (Kaplan and Zingales (1997), Lamont et al. (2001)), the Whited-Wu Index (Whited and Wu (2006)) and an aggregate measure of tightening credit as measured by the spread between interest paid on BAA-rated corporate bonds and AAA-rated ones. The index based measures allow for a division of the firms in the sample into four equally populated centiles which reflect different degrees of likelihood any given firm experiences difficulties in procuring external finance. These are not hard-measures, but if correlated with the unobservable probability of the existence of restrictions to the flow of credit, optimal investment and expenditure behaviour ought to reflect such constraints.

Table 9 summarises the results from previous sections by looking at a wider subgroup of the entire sample than in either preceding case. Absent any suitable instruments, these estimates closely resemble the non-instrumented estimates already discussed, and therefore frame the discussion of how financial constraints might affect research expenditure decisions.

The first measure of constraints analysed is the spread between BAA and AAA corporate bonds. Rather than look at the spread itself, and because it is very likely to be partly driven by the cycle, I generate a series of deviations that are not generated by fluctuations in output. That series is then demeaned and two dummy variables generated from that,

Table 9: R&D ($z_{i,j,t}$) and Sales ($y_{i,j,t}$) / Value Added ($y_{i,j,t}$)

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y_{j,t}$ | 0.542*** | -0.0332 | -0.0639*** |
| | (0.000) | (0.070) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 37982 | 50591 | 48791 |

$p$-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y_{j,t}$ | 0.239*** | -0.121*** | -0.0436*** |
| | (0.000) | (0.000) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 37582 | 48334 | 48217 |

$p$-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y^{+}_{j,t}$ | 0.557*** | -0.0191*** | -0.0769*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^{-}_{j,t}$ | 0.514*** | -0.0593 | -0.0392*** |
| | (0.000) | (0.180) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 37982 | 50591 | 48791 |

$p$-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y^{+}_{j,t}$ | 0.294*** | -0.0943*** | -0.0476*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^{-}_{j,t}$ | 0.161*** | -0.155*** | -0.0378*** |
| | (0.000) | (0.000) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 37582 | 48334 | 48217 |

$p$-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

one for positive and another for negative realisations. Interacting both with the main exogenous regressor gives us two different series: one in which spreads are higher than what would be expected, and one in which they are lower than what would be expected given the behaviour of GDP. Looking at table 10, if these aggregate changes to corporate spreads were to constrain firms in their financing, the coefficients on these two variables should be significantly different from each other. That proposition finds absolutely no support in the data, irrespective of whether we look at sales or value added growth, with no statistically significant differences between the two coefficients in all three models.

Table 10: R&D ($z_{i,j,t}$) and Sales ($y_{i,j,t}$) / Value Added ($y_{i,j,t}$) - BAA-AAA Spread

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y_{j,t}^{sp\uparrow}$ | 0.526*** | -0.0360 | -0.0681*** |
| | (0.000) | (0.093) | (0.000) |
| $\Delta \ln y_{j,t}^{sp\downarrow}$ | 0.552*** | -0.0119*** | -0.0645*** |
| | (0.000) | (0.000) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 36575 | 48002 | 46743 |

$p$-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y_{j,t}^{sp\uparrow}$ | 0.231*** | -0.122*** | -0.0429*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y_{j,t}^{sp\downarrow}$ | 0.230*** | -0.133*** | -0.0454*** |
| | (0.000) | (0.000) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 36247 | 46231 | 46261 |

$p$-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Despite economy wide constraints not appearing to systematically affect firm decisions in terms of R&D spending, it is more than plausible that the aggregate corporate bond spread might have virtually no correlation with each individual firm's financing constraints, which suggests a sufficiently persuasive test of this hypothesis must attempt to measure those at the lower possible level of aggregation. Unfortunately, data on whether firms experience financing difficulties is not available on the Compustat, but the wealth of balance sheet information allows for the creation of artificial or synthetic indexes that have been shown to be correlated with measures of financial constraints. Two of the most influential of these are the Kaplan-Zingales and the Whited-Wu indexes, which combine various information on variables associated with more funds available for investment in an ordering that reflects different underlying probabilities of experiencing difficulties with financing. A discussion of how these are obtained and how the data differs from previous sections can be found in the annex.

In order to test for whether a higher probability of experiencing financial constraints significantly influence the cyclical pattern of R&D, firms in the sample are divided into four different groups according to how high they score on either index, from which four separate series for output growth are then calculated. Interpreting these results mandates an extraordinary degree of caution, given that these indicators are, at best, correlated with unobservable variables of interest, which means evidence in either direction are, at best, indicative of any underlying relationship. That said, and given the high degree of variation in firms' financial health, failure to pick up any difference in the response of R&D expenditure to contemporaneous output variation between the groups would indicate that it is likely other factors play a larger role in determining it.

Table 11: R&D ($z_{i,j,t}$) and Sales ($y_{i,j,t}$) / Value Added ($y_{i,j,t}$) - KZ Index

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y^1_{j,t}$ | 0.545*** | -0.0223*** | -0.0894*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^2_{j,t}$ | 0.495*** | -0.0176*** | -0.0836*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^3_{j,t}$ | 0.547*** | -0.0117*** | -0.0554*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^4_{j,t}$ | 0.633*** | -0.00562*** | -0.0305*** |
| | (0.000) | (0.000) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 36575 | 48002 | 46743 |

$p$-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y^1_{j,t}$ | 0.252*** | -0.204*** | -0.0543*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^2_{j,t}$ | 0.227*** | -0.155*** | -0.0488*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^3_{j,t}$ | 0.236*** | -0.108*** | -0.0414*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^4_{j,t}$ | 0.242*** | -0.0588*** | -0.0194*** |
| | (0.000) | (0.000) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 36247 | 46231 | 46261 |

$p$-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

These results are summarised in tables 11 and 12 for the K-Z and W-W indexes, respectively. With respect to the former, the increasing size in the coefficients shows a slight progression towards a more pronounced pro-cyclical behaviour of growth in R&D as the probability of binding credit constraints increases, but even in firms that have very low probabilities of experiencing any difficulties in obtaining financing, research expenditure is still very strongly pro-cyclical. Running the dynamic models for the ratio of R&D to output and the ratio of R&D to total investment, a similar pattern emerges, with relatively less counter-cyclical behaviour emerging for firms that are more likely to be constrained. Results for the latter are somewhat harder to interpret: higher probability of financial constraints are associated with *less* pro-cyclical research spending, measured by its growth rate, while in both dynamic models the higher likelihood of experiencing constraints leads to a less counter-cyclical effect.

Though somewhat puzzling, a plausible explanation for these results lies with the fact that when divided using the W-W index, more financially constrained firms also experience much lower growth rates of sales and value added, which in turn may be why they are more reliant on outside financing. That would explain why they would respond much less to fluctuations in sales, as they are less dependent on them anyway, and why they would be unable to smooth investment in R&D as much as they would like to, which leads to less counter-cyclical behaviour.

Table 12: R&D ($z_{i,j,t}$) and Sales ($y_{i,j,t}$) / Value Added ($y_{i,j,t}$) - WW Index

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y^1_{j,t}$ | 0.577*** | -0.0216*** | -0.0906*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^2_{j,t}$ | 0.564*** | -0.0123*** | -0.0734*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^3_{j,t}$ | 0.517*** | -0.0118*** | -0.0576*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^4_{j,t}$ | 0.490*** | -0.00943*** | -0.0415*** |
| | (0.000) | (0.000) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 36575 | 48002 | 46743 |

$p$-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

| | (1) | (2) | (3) |
|---|---|---|---|
| | $\Delta \ln z_{i,j,t}$ | $s_{i,j,t}$ | $z\|i_{i,j,t}$ |
| Lags | - | (2) | (2) |
| $\Delta \ln y^1_{j,t}$ | 0.326*** | -0.154*** | -0.0587*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^2_{j,t}$ | 0.284*** | -0.133*** | -0.0437*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^3_{j,t}$ | 0.199*** | -0.140*** | -0.0371*** |
| | (0.000) | (0.000) | (0.000) |
| $\Delta \ln y^4_{j,t}$ | 0.101*** | -0.107*** | -0.0358*** |
| | (0.000) | (0.000) | (0.000) |
| Controls | Y | Y | Y |
| FE | Y | Y | Y |
| Year FE | Y | Y | Y |
| $N$ | 36247 | 46231 | 46261 |

$p$-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Although there is slight evidence that these constraints affect firm behaviour, the data suggest that they do not significantly disrupt the channels identified previously, i.e., that there is some degree of 'smoothing' in research expenditure and that it tends to, largely, track the growth rate of output throughout the cycle. Constraints to firms' ability to finance these expenditures play a role in limiting the degree of smoothing that they engage in, but the data do not seem to corroborate the view that, absent these, research expenditures would exhibit a counter-cyclical pattern.

## 5. Discussion

Taking stock of the results discussed in the preceding section allows us to revisit the quasi-stylised facts outlined in the introductory gambit, and provide, in light of their robustness, a more generalised picture of the behaviour of research spending throughout the cycle and tentatively settle the debate over what its main drivers are. The first of those proposed quasi-stylised facts is confirmed by the data, which shows that research expenditure tracks changes in output (whether it is measured in value added or sales) and that it does so even when controlling for the potential co-determination through the use of an instrument for the measure of output.

The second of those assertions argued that despite the markedly pro-cyclical behaviour, the 'opportunity cost' hypothesis would most likely manifest itself through expenditure smoothing. In other words, rather than *decrease* the level of research effort in response to an *increase* in output, firms' find it optimal to decrease the share of R&D to output, as well as devoting more resources, proportionally, to capital investments. This hypothesis is also confirmed by the results discussed in this paper, and it provides both confirmation to the idea that there is 'R&D smoothing' throughout the cycle and a more consistent framework to make sense of competing claims regarding the cyclical nature of that spending: it depends on what measure is used.

Some authors have tried to reconcile Schumpeter's original idea by suggesting that while firms would ideally increase their research efforts during periods of diminished economic activity if unconstrained, restrictions to the availability of funds, generated internally or through access to capital and debt markets, hamper their ability to do so, thereby inducing a more pro-cyclical response in research activity than would otherwise be observed. This argument lends itself to two straightforward conclusions: the response of R&D must be asymmetrical depending on whether output is at a trough or peak[17], and more financially

[17]Evidently, higher sales growth does not inhibit firms in their decision to spend less on R&D.

constrained firms should behave significantly differently from unconstrained ones in what concerns their spending decisions.

In evaluating both claims, the data fails to provide results as robust as those outlined in the two opening paragraphs of this section, but it would not be disingenuous to assert that there is little to no evidence of an asymmetric response that is systematically obeyed. Indeed, the only instance when this particular theory is validated is at the industry level, when the growth rate of value added is instrumented by the growth rate of real GDP, which turns out not to be statistically significant. All other models fail to report a pattern of pro-cyclical behaviour during periods of negative growth and counter-cyclical R&D during expansions of output. This does not indicate that firms do not finance expenditure through earnings, however; if the main driver of research spending is changes in output, then even if the former is true, innovative activity should always track the business cycle. Funds generated through profits might be important in providing the financing, but there is no suggestion in the results discussed here that is the main determinant of the decision to invest or not.

Finally, another caveat is required when discussing the issue of financial constraints: absent observable data on firms' hitting a borrowing constraint, any discussion of this topic must acknowledge the inherent limitations in any variable's information content in this respect. The use of synthetic indexes warrants further caution, and therefore the interpretation of these results should remain, at best tentative; nevertheless, provided there is a reasonable expectation that they carry useful information in this respect , they provide important clues as to the likelihood of these explanations as being particularly powerful.

With those cautions in mind, the results presented herein unanimously point in the direction of a negligible impact of these constraints on the degree to which financial constraints are a significant driver of pro-cyclical R&D. This is not equivalent to arguing that these do not matter or that some firms, particularly less established ones, do not face binding borrowing constraints; what is argued in this paper is that the existence of these does not contribute significantly to the cyclicality of R&D, as much as our imperfect measures allows to infer.

## 6. Conclusion

The cyclical pattern of research spending has long been thought of as an important stepping stone in our understanding of business cycles and their consequences. Evidence of strongly pro-cyclical R&D could mean that very sharp fluctuations in output have long lasting effects by depressing investment in inventive activity, which would in turn likely impact on the economy's medium to long term growth prospects. A majority of previous empirical work tentatively settled on a consensus view that R&D behaved pro-cyclically, but recent work dissented from this view, and particularly reinforced the view that financial constraints play a large role in driving this feature of the data.

In this paper, a three-pronged approach to this problem is suggested: using three different measures of the response of R&D to changes in output, a clearer picture of its behaviour across the cycle can be drawn. The first set of findings strongly suggests that the main driver of research expenditures is output growth and that firms smooth those expenditures across the business cycle, implying that despite being pro-cyclical, R&D spending does not fluctuate nearly as much as output and that its share behaves counter-cyclically. This means that although sharp fluctuations may lead to reasonably large variations in research expenditure, there are built-in stabilisers that ensure the long-run effects of aggregate fluctuations are minimised. By examining the ratio of R&D to total investment, defined as the sum of capital and research expenditures, the results discussed throughout strongly suggests that firms' share of investment on innovation behaves counter-cyclically as well, this providing some confirmation of the existence of an 'opportunity cost' hypothesis: higher output growth increases expenditure in all dimensions - a rising tide lifts all boats -, but increases in research expenditure are much smaller than increases in capital expenditure.

A separate issue concerns the role financing plays in driving the observed pro-cyclical behaviour of R&D. Both internal finance [18] and external borrowing constraints might prevent firms from adjusting optimally to fluctuations in output. Throughout this paper, the first of these hypothesis is tested by looking at asymmetric responses of research spending depending on what phase of the cycle firms are in, and no significant corroborating evidence in favour of this hypothesis was found in any of the models. Measures of firms' exposure or implied probability of experiencing external finance constraints were also used

[18] Lower sales/value added mean less cash availability for financing expenditure.

in trying to ascertain whether they played a large role in driving the cyclical pattern of R&D and, again, the evidence suggests that while it may restrict firms' optimal levels of spending, it is not a main cause for that statistical feature.

## References

Philippe Aghion, Philippe Askenazy, Nicolas Berman, Gilbert Cette, and Laurent Eymard. Credit constraints and the cyclicality of r&d investment: Evidence from france. *Journal of the European Economic Association*, 10(5):1001–1024, 2012. ISSN 1542-4774. doi: 10.1111/j.1542-4774.2012.01093.x. URL `http://dx.doi.org/10.1111/j.1542-4774.2012.01093.x`.

Gadi Barlevy. On the cyclicality of research and development. *American Economic Review*, 97(4):1131–1164, September 2007. URL `http://ideas.repec.org/a/aea/aecrev/v97y2007i4p1131-1164.html`.

E. Bartelsman, R. Becker, and W. Gray. The NBER-CES manufacturing industry database. Technical report, NBER, 1996.

Derek Bosworth and Tony Westaway. The influence of demand and supply side pressures on the quantity and quality of inventive activity. *Applied Economics*, 16(1):131–146, 1984. doi: 10.1080/00036848400000012. URL `http://www.tandfonline.com/doi/abs/10.1080/00036848400000012`.

Simona Bovha-Padilla, Joze P. Damijan, and Jozef Konings. Financial constraints and the cyclicality of ṛinvestment:evidence from slovenia. LICOS Discussion Papers 23909, LICOS - Centre for Institutions and Economic Performance, KU Leuven, 2009. URL `http://ideas.repec.org/p/lic/licosd/23909.html`.

James R. Brown and Bruce C. Petersen. Cash holdings and r&d smoothing. *Journal of Corporate Finance*, 17(3):694 – 709, 2011. ISSN 0929-1199. doi: 10.1016/j.jcorpfin.2010.01.003. URL `http://www.sciencedirect.com/science/article/pii/S0929119910000040`. ¡ce:title¿Financial Flexibility and Corporate Liquidity¡/ce:title¿.

P A Geroski and C F Walters. Innovative activity over the business cycle. *Economic Journal*, 105(431):916–28, July 1995. URL `http://ideas.repec.org/a/ecj/econjl/v105y1995i431p916-28.html`.

Charles J. Hadlock and Joshua R. Pierce. New evidence on measuring financial constraints: Moving beyond the kz index. *Review of Financial Studies*, 23(5):1909–1940, 2010. doi: 10.1093/rfs/hhq009. URL `http://rfs.oxfordjournals.org/content/23/5/1909.abstract`.

Charles P. Himmelberg and Bruce C. Petersen. 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, 1994. ISSN 00346535. URL http://www.jstor.org/stable/2109824.

Ayse Imrohoroglu and Selale Tuzel. Firm level productivity, risk, and return. 2011 Meeting Papers 21, Society for Economic Dynamics, 1 2011. URL http://ideas.repec.org/p/red/sed011/21.html.

Steven N. Kaplan and Luigi Zingales. Do investment-cash flow sensitivities provide useful measures of financing constraints? *The Quarterly Journal of Economics*, 112(1):169–215, 1997. doi: 10.1162/003355397555163. URL http://qje.oxfordjournals.org/content/112/1/169.abstract.

Alfred Kleinknecht and Bart Verspagen. Demand and innovation: Schmookler re-examined. *Research Policy*, 19(4):387–394, August 1990. URL http://ideas.repec.org/a/eee/respol/v19y1990i4p387-394.html.

Owen Lamont, Christopher Polk, and Jesus Saa-Requejo. Financial constraints and stock returns. *Review of Financial Studies*, 14(2):529–54, 2001. URL http://ideas.repec.org/a/oup/rfinst/v14y2001i2p529-54.html.

Kadri Männasoo and Jaanika Meriküll. How do demand fluctations and credit constraints affect r&d? evidence from central, southern and eastern europe. Bank of Estonia Working Papers wp2011-09, Bank of Estonia, July 2011. URL http://ideas.repec.org/p/eea/boewps/wp2011-09.html.

Min Ouyang. On the cyclicality of r&d: disaggregated evidence. *The Review of Economics and Statistics*, 93(2):542–553, May 2011. URL http://ideas.repec.org/a/tpr/restat/v93y2011i2p542-553.html.

Matthew Rafferty and Mark Funk. Demand shocks and firm-financed r&d expenditures. *Applied Economics*, 36(14):1529–1536, 2004. doi: 10.1080/0003684042000217959. URL http://www.tandfonline.com/doi/abs/10.1080/0003684042000217959.

Gilles Saint-Paul. Productivity growth and the structure of the business cycle. *European Economic Review*, 37(4):861 – 883, 1993. ISSN 0014-2921. doi: 10.1016/0014-2921(93)90095-R. URL http://www.sciencedirect.com/science/article/pii/001429219390095R.

F. M. Scherer. Demand-pull and technological invention: Schmookler revisted. *The Journal of Industrial Economics*, 30(3):pp. 225–237, 1982. ISSN 00221821. URL http://www.jstor.org/stable/2098216.

Jacob Schmookler. *Invention and economic growth*. Harvard University Press, 1966.

Joseph Alois Schumpeter. *Business cycles: a theoretical, historical, and statistical analysis of the capitalist process*. McGraw-Hill Book Company, inc., 1939. URL http://books.google.pt/books?id=9-JdAAAAIAAJ.

Klaus Wälde and Ulrich Woitek. R&d expenditure in g7 countries and the implications for endogenous fluctuations and growth. *Economics Letters*, 82(1):91–97, January 2004. URL http://ideas.repec.org/a/eee/ecolet/v82y2004i1p91-97.html.

Toni M. Whited and Guojun Wu. Financial constraints risk. *Review of Financial Studies*, 19(2):531–559, 2006. URL http://ideas.repec.org/a/oup/rfinst/v19y2006i2p531-559.html.

## Appendix A. Data sources

A.1. **Aggregate data.** The aggregate time series used throughout this paper were collected from three main sources, the BEA's NIPA tables, the Federal Reserve Bank of St. Louis (FRED) and the Social Security Administration. From these, I extracted the series on current price GDP and GDP deflator (BEA NIPA), data on corporate bond yields for AAA rated, BAA rated and government bonds (FRED), and average wages (SSA). All series were collected for the period from 1958 to 2011.

A.2. **Industry data.** Data on total, company and federal research spending by industry was taken from the NSF's Iris, for the period between 1953 and 1998. This allowed me, following Ouyang (2011), to compile a time series for real growth in company funded R&D for the following 20 industries:

Table 13: Industry name and code

| Name | SIC code |
|---|---|
| Food | 20—21 |
| Textiles | 22—23 |
| Lumber | 24—25 |
| Paper | 26 |
| Industrial Chemicals | 28.1-82,28.6 |
| Drugs | 28.3 |
| Other Chemicals | 28.4-85,28.7-89 |
| Petroleum refining and Extraction | 13—29 |
| Rubber | 30 |
| Stone | 32 |
| Ferrous Metals | 33.1-33.2,33.98-33.99 |
| Non-ferrous Metals | 33.3-33.6 |
| Metal Products | 34 |
| Machinery | 35 |
| Other electrical equipment | 36.1-36.4,36.9 |
| Electronics & Communication | 36.6-36.7 |
| Autos & Others | 37.1,37.3-7.5,36.9 |
| Aerospace | 37.2,37.6 |
| Scientific instruments | 38.1-38.2 |
| Other instruments | 38.4-38.7 |

Information on value added is taken from the 1987 SIC version of the NBER Manufacturing Productivity Database, which spans the timeframe between 1958 through to 2009. Value added data is disaggregated at the fourth digit in the database, allowing for the construction of series that encompass the same industries as the R&D series. Apart from value added and value of shipments data, the database includes information on capital expenditure (investment), equipment, plant and total capital value, and payroll data. All of these variables are deflated using their respective deflators (available in the database).

Due to privacy concerns, values for company financed R&D in certain years are omitted from the series, which significantly decreases the quality of the data. In order to circumvent this problem, and because total R&D or federally funded R&D are included whenever company spending isn't, I use multiple imputation to generate estimates of the latter whenever these are unavailable. Those then replace omitted values in the data to create a complete series. In all regressions, both series are used to ensure that results are not dramatically altered by using the imputed series. The raw values are then deflated using the GDP deflator from the BEA NIPA tables and growth rates computed. Using the composite SIC codes in table 13, this is then merged with the value added series to complete the industry level database, to which the real growth rate of GDP is added to be used as an instrument.

An additional source of data at the industry level are two historical series on value added and gross output from the BEA's Annual Industry Accounts. These series are disaggregated using NAICS codes at the three digit level and include non-manufacturing industries:

A.3. **Compustat data.** At the firm level information, except where noted, comes from the Compustat database. All variables were deflated using the GDP deflator taken from the BEA NIPA series where appropriate and growth rates computed for the variables of interest. The variables collected are described in table 14:

Value added is computed using two different metrics, as discussed in Imrohoroglu and Tuzel (2011). The first makes use only of information available in the Compustat database, and is calculated as the sum of Staff Expense (xlr) and Operating Income Before Depreciation (oibdp). This significantly reduces the number of observations, which motivates using an approximation to the total wage bill for each firm using the average wage index series published by the Social Security Administration. A synthetic value added

Table 14: Compustat variable and abbreviation

| Name | Abbreviation | Name | Abbreviation |
|---|---|---|---|
| Assets | at | Capital Expenditure | capx |
| Common/Ordinary Equity | ceq | Cash and Short-Term Investments | che |
| Long-Term Debt Due in One Year | dd1 | Debt in Current Liabilities | dlc |
| Long-Term Debt | dltt | Depreciation and Amortization | dp |
| Dividends Common/Ordinary | dvc | Dividends - Preferred/Preference | dvp |
| Employees | emp | Income Before Extraordinary Items | ib |
| Liabilities | lt | Operating Income Before Depreciation | oibdp |
| Sales/Turnover (Net) | sale | Property, Plant and Equipment (Net) | ppent |
| Stockholders Equity - Parent | seq | Deferred Taxes (Balance Sheet) | txdb |
| Staff Expense | xlr | Research and Development Expense | xrd |
| Staff Expense - Wages and Salaries | xstfws | NAICS | naics |

measure is then calculated using this information[19]. The Kaplan-Zingales and Whited-Wu indexes were calculated using only balance sheet information and, for the latter, an aggregate of industry value added was built by adding up firm value added for each three digit NAICS code.

## Appendix B. Details and robustness checks

B.1. **Industry Data - Manufacturing.** The approach in this section closely follows the work of Ouyang (2011), but fails to provide confirmation of the results in her contribution. Instead of using an interpolation of the raw R&D data for each industry the series in this paper are completed using multiple imputation and reported results are for the raw data only, which is why the results differ from previous research. As with the interpolated data, imputed data yields tighter distributions around each point estimate, which means standard deviations are smaller and common significance thresholds are reached. Despite that, p-values are consistently near the 10% mark, which means including controls and/or using the raw data leads to a failure to reject the null hypothesis. All regression models are estimated using alternative methods, namely difference and system GMM for the dynamic models, which yield qualitatively identical outcomes. A final robustness check

[19]As in Imrohoroglu and Tuzel (2011), this synthetic measure fares reasonably well as an approximation to real value added, as indicated by the very strong correlation between the two.

comes from applying a Hodrick-Prescott filter to extract deviations from trend and using those as replacements for the growth rates of R&D and the output variables in the regressions. Again, this does not qualitatively change the results. The controls used for all the regressions in this section are as follows: firm size (measure by the number of employees), the contemporary and lagged real value of equipment and the contemporary and lagged plant values in real terms. Year dummies and fixed effects are used when specified in the main text.

B.2. **Firm Data (Compustat) - Manufacturing.** The controls included in all of the regressions in this section include a measure of firm size (number of employees) and contemporary values and two lags of the following balance sheet / cash flow data: total assets, total liabilities, long-term debt, long-term debt due in one year, property, plant and equipment and cash (measured as the sum of cash and short-term investments and investment in R&D). Given the gaps in the data, it isn't possible to use a Hodrick-Prescott filter in order to extract the deviations. Alternatively, I use the in-group time average and calculate the difference from that average. Using this variable rather than the growth rate for R&D expenditure and any of the output variables doesn't qualitatively change the results. As with the industry data, alternative estimation methods are used for the dynamic models, as well as clustered standard errors on both firm and industry identifier. None of these alternative specifications change any of the main results in any qualitative sense.

B.3. **Firm Data (Compustat) - All Industries.** All regressions in this section use the same controls as in the preceding one, and the standard robustness checks of clustering standard errors on both the firm and industry identifiers yield similar results. Estimation with system and difference GMM estimators yield qualitatively identical results to those outlined in the main text. Demeaned (*en lieu* of detrended) data also corroborates all of the main findings.

B.4. **Firm Data (Compustat) - Financial Constraints.** The indexes used throughout this section in the main text can be found in Lamont et al. (2001), for the K-Z index and Whited and Wu (2006), for the eponymous W-W index. The former is calculated using the following formula:

$$KZ = -1.001909 \cdot CF + 0.2826389 \cdot Q + 3.139193 \cdot D - 39.3678 \cdot Div - 1.314759 \cdot Cash$$

Where $CF$ is the ratio of cash-flow (income before extraordinary items + depreciation and amortisation) to physical capital [20], $Q$ is Tobin's Q (total assets at+market value-common equity-deferred taxed/total assets), $D$ is total debt (long-term debt+debt in current liabilities/stockholders equity - parent + lont-term debt + debt in current liabilities), $Div$ is the ratio of dividends to physical capital and $Cash$ is the ratio of cash and liquid assets to physical capital. The W-W index, in turn, is calculated as:

$$WW = -0.091 \cdot CF - 0.062 \cdot DP + 0.021 \cdot D - 0.044 \cdot ln(A) + 0.102 \cdot Sale_i - 0.035 \cdot Sale$$

Here, $CF$ is defined as above, $DP$ is an indicator variable for whether dividends were paid by that firm that year, $D$ is debt, also defined as above, $A$ is total assets, $Sale_i$ is the growth rate of sales for the industry[21] and, finally, $Sale$ is the growth rate of sales for the firm.

For both indexes, firms are separated according to which quartile they belong to, and four auxiliary variables created indicating the quartile to which any given observation belongs. By interacting each indicator variables with the growth rate variable we get four series ranked according to likelihood of experiencing financial constraints.

Finally, a third set of measure used is the spread between AAA-rated and BAA-rated bonds and government expenditure. In order to extract information about tightening conditions that are independent from the effect of the cycle, these spreads are then regressed on output growth and the errors used as a measure of the tightness of credit constraints. If the errors take on positive values, this implies tighter conditions than what would be justified by the business cycle, with the reverse holding for negative values. An indicator variable is created for each and both interacted with the growth rate of the output variable. Doing so allows for the same exercise as with the K-Z and W-W indexes: any systematic differences ought to be picked up by the difference in the estimates.

[20] Physical capital is always lagged one period in this formula and is measured as Property, Plant and Equipment (Net).

[21] Industry here is defined as the NAICS code at the 3-digit level. As mentioned elsewhere, total sales are added up for all the firms belonging to the 3-digit group and the real growth rate calculated from that.