Expectations and R&D investments over the firm's business cycle.*

Davide Arnaudo, Diego Scalise, Giulia M. Tanzi†

January 9, 2014

Abstract

This work studies how entrepreneurs adjust R&D investments over the business cycle on the basis of their expectations for business developments and their attitude towards the future. It does this by applying a System GMM estimator with Heckman correction to a panel of Italian manufacturing firms over the period 2000-2011, dealing at the same time with persistence and selectivity in R&D expenditure. Our main results, robust to a variety of ancillary tests, are as follows. First, entrepreneurs' expectations for the future help to explain firms' R&D investments, while the firm-level business cycle itself is not fully informative. Specifically, firms' innovative effort reacts pro-cyclically with respect to their forecasts for business performance. Second, expectations have a particularly strong impact on the choices of older firms and of those that operate in less volatile sectors. This suggests that firms' R&D investments increase when, thanks to their experience or to a stable environment, they can reasonably believe in their expectations. Policy measures aimed at sustaining innovation by firms during the business cycle need to take into account the different degree of sensitivity to expectations shown by firms belonging to different sectors.

JEL classification: G23, D84, E32, 030.

keywords: business cycle, expectation, research and development.

*We thank Matteo Bugamelli, Massimo Gallo, Bronwyn Hall, Sergi Jiménez-Martín, Francesca Lotti, Paola Rossi, Francesco Venturini and all participants in the Bank of Italy Workshop on the Microeconometrics of Innovation, Rome, 12-13 March 2012 and the Workshop on Innovation in Italy, Perugia, 13-14 December 2012, for helpful comments and suggestions. The opinions expressed in this paper are the authors' and do not necessarily represent those of the Bank of Italy. The authors alone are responsible for any errors.

†Bank of Italy, Milan Branch, Economic and Regional Analysis and Research Division

1 Introduction

How do expectations for future sales affect firms' R&D strategies? More precisely, how do firms select and adjust R&D investments on the basis of expected business conditions? In this paper we empirically investigate how firms' predictions regarding future demand for their products affect R&D expenditure, on the reasonable expectation that entrepreneurs' forecasts about business developments add important information about key strategic choices, such as how much to spend on R&D. This paper is related to the strand of the economic literature that studies the response of R&D investments to the economic cycle (Aghion et al., 2012; Barlevy, 2007; Comin and Gertler, 2006; Griliches, 1990). From the theoretical point of view, the issue of how R&D expenditure responds to the business cycle is a matter of controversy. On the one hand, such investment may follow the business cycle, with cutbacks during downturns as financial resources become less available. On the other, during a recession the opportunity cost of R&D investments in terms of forgone output diminishes, which could foster the allocation of resources to innovative activities that sustain long-run productivity growth.

This work makes a twofold contribution to the standard empirical approach to this relationship. First, we add an important piece to the empirical picture by explicitly studying the role of firms' expected future performance, and not just past and current performance, as a determinant of R&D patterns. Previous studies in this field have neglected firms' expectations, mainly because of the lack of data at firm level. We base our analysis on different waves of the Survey of Industrial and Service Firms, conducted annually by the Bank of Italy on a sample of some 4,000 firms. Firms participating in the Survey not only provide information on the firm's structure, operations and main economic indicators, but are also asked to offer forecasts regarding the evolution of the firm's activity. And since the Survey tracks the same firms over time, data on expectations vary not only across firms but also over time, capturing the relation between the expected business cycle and R&D choices. Secondly, we enrich the standard approach from an econometric point of view: to the best of our knowledge, this is the first attempt to study R&D behaviour at micro level while also dealing with selectivity and persistence in R&D expenditure. In examining how R&D expenditure behaves over the business cycle, we apply a System GMM estimation strategy with Heckman selection (as in Jiménez-Martín, 2006) to an unbalanced panel of around 1,100 Italian manufacturing firms in the period 2000-2011.

Our results, robust to a wide variety of auxiliary regressions and tests, suggest that what matters in shaping R&D investments is not the actual evolution of the firm's business cycle, as typically pointed out in the literature, but firms' expectations of its trend. In particular, a positive effect is found for the expected business conditions: forecasts of rising sales foster innovative efforts by firms. R&D expenditure appears to be pro-cyclical with respect to expectations. In addition, we find that when firms realize they have made mistakes in forecasting (actual sales diverge from expectations owing to a demand shock or to entrepreneurs' mistaken presentiments) they do not react by adjusting R&D investments. This result, again, supports the view that what matters in shaping R&D behaviour is firms' expectations rather than actual realizations. Observed realization can be decomposed into the sum of expected sales growth and the forecast error (see Section 3 for the analytical decomposition). The mixed results of previous studies of the relationship between observed business cycle and R&D investments may also be due to a failure to properly disentangle the effects of these two components (thereby introducing noise into the effect of the composite variable). Moreover, we find evidence that expectations play a stronger role in determining R&D choices for older firms and for businesses in sectors subject to a lower degree of uncertainty. Firms tend to increase R&D investments when they can more reasonably believe in favourable conditions on the strength of their experience or thanks to more stable market conditions. As a consequence, for a proper assessment of the effect of firms' expectations for the future on innovative effort, it is necessary to take into account the structure of the economy in terms of the age of firms and the sectors to which they belong. In line with the most recent finding in the literature (i.e. Aghion et al., 2012) we also investigate the role of credit constraints: a rationed firm invests less in R&D than a non rationed counterpart with the same expectation for the future.

In summary, our results suggest that expectations are crucial for firms in determining how much to spend on R&D: enterpreneurs use R&D investments strategically during the economic cycle to define their competitive position in accordance with their predictions and insofar as they can reasonably believe in the forecast. Policies aimed at increasing investments in R&D should be designed to take into account firms' responses to expected business conditions, which differ significantly across firms. For example, measures intended to maximize the overall investment in innovation in an environment where favourable expectations prevail should be targeted to older firms and to businesses in less uncertain sectors, since such firms are likely to respond more promptly with R&D investments to positive economic prospects. On the contrary, when hard times are predicted, the same firms will respond to unfavourable expectations by curtailing investments in innovation more drastically than businesses in less stable sectors, so the policy action has to exert a stronger effort on them in order to produce the same overall impact on R&D.

The next section reviews the relevant literature. Section 3 describes the data and provides summary statistics. Section 4 discusses the econometric specification and the main methodological choices. Section 5 sets out the main econometric evidence and Section 6 details the robustness checks performed. Section 7 concludes.

2 Literature Review

The impact of economic downturns on the dynamics of R&D investment is a matter of controversy in the literature. A number of theories explains why R&D spending could be pro-cyclical. For example, Barlevy (2007) develops a stochastic Schumpeterian growth model in which, although it is socially optimal for R&D to be concentrated during downturns, short-term behaviour by innovators results in an inefficiently pro-cyclical allocation of resources to R&D. In a business cycle model with endogenous R&D spending, Comin and Gertler (2006) find that exogenous mark-up shocks can also induce pro-cyclical movements in R&D. According to the Schumpeterian concept of creative destruction, instead, recessions foster firms to search for higher productivity, through various activities such as reorganization, training, and research and development, because their opportunity costs are lower than in boom (Aghion and Saint-Paul, 1998). R&D expenditure should hence be countercyclical: firms devote more resources to R&D in troubled times, while reducing during expansionary phases of the cycles. Bloom (2007) shows that also differences in the adjustment cost, with respect to other kind of investment, could reduce the responsiveness of R&D to changes in demand conditions and increase the persistence over time at higher uncertainty.

Not only in theoretical debate, but also in the empirical literature, R&D expenditure path over business cycle remains ambiguous. Many works have dealt with this issue stressing the role of financial factors and credit markets imperfections. In particular, Aghion et al. (2005), based on cross-country panel data, find that investments are less countercyclical in countries with lower ratios of credit to GDP. In a successive work Aghion et al. (2012), using French firm-level data, show that R&D investments turn to be more pro-cyclical as firms face tighter credit constraints, while, in the absence of constraints, R&D appears to be countercyclical. López-García et al. (2012), using a panel of Spanish firms, find that the R&D behaviour varies among firms with different access to credit, and that this also turns out to be true when looking at the cyclicality of training spending and of patent purchases.

Our work moves from the most recent findings in the literature to add new important variables that are likely to matter in explaining the R&D paths over time. Among these firms' expectations about their business cycle have been scarcely considered in the economic literature due to the unavailability of data at firm level. One of the few works on the topic is Hartl and Herrmann (2006) that study new product introductions in the German food industry, finding a negative effect of positive expectations for the future on the development of new ideas. Durand (2003) focuses on forecast errors instead of expectations, and examines inter-firm differences in forecasting errors on a sample of French companies and their effects, among others, on R&D expenditure. He finds evidence that larger forecast errors correspond to higher R&D investments. Another recent attempt to deal with the issue is D'Aurizio and Iezzi (2011), who analyze and model Italian firms' ability to predict future investments using two consecutive waves of the Bank of Italy Survey of Industrial and Service Firms to match investment plans and realisations for each firm.

While scarcely considered in the economics literature, expectations have been vastly studied in the management literature. In this context, forecasting ability appears to be a distinctive organizational capability and one of the key factor of a firm's success (Makadok and Walker, 2000; Eisenhardt and Martin, 2000). Moreover, it has also been shown that managerial optimism and overconfidence significantly affect corporate investment (Malmendier and Tate, 2005; Lin et al., 2005; Glaser et al., 2007).

Summing up, neglecting the role of firms' expectation means loosing a potentially important part of the picture about the behaviour of R&D investments, also given the unclear relationship between firm's business cycle and R&D investment.

3 Data and variables

We constructe our sample from the Survey of Industrial and Service Firms, conducted every year by Bank of Italy since 1978 with the scope to gather quantitative data on the most important variables for the firm's activity. The sample, which includes industrial and services firms with at least 20 employees, is broadly representative of the structural composition of the Italian economy (being stratified according to sector, size and geographical location). Data are collected at the beginning of each year, relative to the previous year, and special effort is made to keep information as closely comparable as possible in subsequent waves of the survey. Interestingly, for some variables (such as investments and sales) firms are asked to provide forecasts for their business evolution along the year. Since the respondent of the Survey is either the firm's owner or a member of its top management, except for very large firms, forecasts and expectations are likely to reflect the perceptions of a person with direct responsibility for firms' decisions[1]. Moreover, because in the different waves of the Survey the same firm is followed over time, it is possible to compare realizations with the previous period forecasts. We merge this dataset with information on balance sheet coming from the official records elaborated by Cerved group (Company Account Data Service, CADS), in order to add other financial variables to our analysis. We focus on manufacturing because most corporate R&D expenditure occurs in this sector. Moreover, we restrict the estimation sample to firms with 50 or more employees, covering the period 2000-2011 and around 1,100 firms[2]. We report the definitions, summary statistics and the correlation matrix for the variables used in the analysis in table 1, 2 and 3. All variables are expressed in real terms.

Since the main contribution of this work is to analyze in depth the linkages between expectations formation over the business cycle and investments in R&D, we focus now on describing the variables related to firms expectations. We consider firm's expectation in $t-1$ for sales growth between $t-1$ and t: this variable represents the way the business cycle is perceived by the firm, perception that may be crucial in determining investment choices, in addition to the evolution of the past and current business performance of the firm. Starting from expectations for the next year we can construct forecasting errors, that is made of the difference between realized sales in the period t and sales expected in $t-1$ for t, divided by this last term (such that we have a forecast error in percentage term). A positive error (higher realized sales than predicted) corresponds to a pessimistic mood of the entrepreneur toward future or to the occurrence of an unexpected positive shock that affected the firm's sales. The contrary holds for a negative forecasting error, while an error close to zero implies high accuracy in forecasting. As show in table 4, we observe that, on average, firms

[1] In the case of big companies, the interview is typically carried out with a representative of the administrative area. In this case, forecasts reflect the economic budget formulated for the year of the interview by the board of directors of the company itself.

[2] From 2001 and 2002 the survey was extended to include, respectively, firms with at least 20 employees and non-financial private service firms. However, for small firms and service companies, information on R&D investments is available only starting from 2010. Thus, we focus the analysis on manufacturing firms with 50 or more employees to keep the sample as homogeneous as possible along all the time dimension.

tend to overestimate future sales: sales' realizations are 1.4 per cent lower than forecasts. Moving to the absolute values of these forecast errors, we find that the average absolute error is around 9.5 per cent of the sales. In the last recession (2008-2009) the average precision of forecasts sharply declined, suggesting that this episode was not fully and properly anticipated by firms (expectations much higher than realizations). Conditioning on sector, firms belonging to the food product, beverages and tobacco sectors are characterized by the highest forecasting ability, that can be related to the low variability of demand that is typically associated to these sectors. On the contrary, firms belonging to basic metals, engineering sector and to the non-metallic minerals industry show, on average, higher difficulty to predict future business conditions. The lowest accuracy in prediction is reported for the entrepreneurs whose firm is located in the South of Italy, while those from the North East of Italy show the best forecasting performances.

As previously mentioned, the literature has focused on the effects on R&D expenditures of the firm's business cycle, that is measured as the sales growth rate between $t-1$ and t. With simple mate, the sales growth rate can be seen as the sum of the expected sales growth rate and of the forecast error. In fact, by definition:

$$\Delta S_t = \frac{S_t - S_{t-1}}{S_{t-1}} \approx ln\left(\frac{S_t}{S_{t-1}}\right)$$

Adding and subtracting the logarithm of the expected sales in $t-1$ for t, we can rewrite it as:

$$\begin{aligned} ln\left(\frac{S_t}{S_{t-1}}\right) &= ln\left(S_t\right) - ln\left(E_{t-1}S_t\right) + ln\left(E_{t-1}S_t\right) - ln\left(S_{t-1}\right) \\ &= ln\left(\frac{E_{t-1}S_t}{S_{t-1}}\right) + ln\left(\frac{S_t}{E_{t-1}S_t}\right) \end{aligned}$$

These terms are the logarithmic approximations of the sales growth rate expected at time $t-1$ and the forecasting error, the two variables we are going to include in our estimation

$$\begin{aligned} E_{t-1}\Delta S_t &= \frac{E_{t-1}S_t - S_{t-1}}{S_{t-1}} = ln\left(\frac{E_{t-1}S_t}{S_{t-1}}\right) \\ err_t &= \frac{S_t - E_{t-1}S_t}{E_{t-1}S_t} = ln\left(\frac{S_t}{E_{t-1}S_t}\right) \end{aligned}$$

Observed sales growth rate hides two distinct elements which have not been studied in isolation by previous studies; the ambiguity of results in the literature on the relationship between R&D investment and firm's business cycle could hence derive also from potentially diverging effects of the two components. Decomposing the sales growth rate and separating the effects of expectations may help in better understanding R&D responses to the business cycle.

4 Specification and empirical strategy

Our basic specification is the following:

$$RD_{it} \;=\; \beta_1\, RD_{it-1} + \underbrace{\beta_2\, \Delta S_{it}}_{=\beta_2 E_{it-1}(\Delta S_{it})+\beta_3 err_{it}} + \beta_4\, X_{it} + u_i + \delta_t + \varepsilon_{it}.$$

where the dependent variable is the innovative effort of the firm, proxied by the level of R&D expenditure in period t (we took the logarithm of $1 + R\&D$). The first covariate is simply the lagged value of R&D, in order to control for persistency in R&D expenditure[3]. Then, we include sales growth between $t-1$ and t, to capture the impact on R&D investments of the business cycle evolution. Instead of considering, as in previous studies, only the firms' observed conditions, we substitute sales growth from $t-1$ to t with our variables of interest that capture the expectation formed in $t-1$ for t. We then include other time varying firm characteristics, such as age and the average number of employees (to control for the size since the dependent variable is in level). In the robustness section we include the financial variables that can influence R&D choices and that are typically included as regressors in the literature: the cash flow generated by the firm and two measures of credit constraints. The model includes a firm specific effect (u_i) to take into account all unobserved time-invariant firm's characteristics that can influence the amount of R&D expenditure (like, for example, sector, geographic location). Finally, we account for time effect by including a full set of year dummies (δ_t).

In estimating this equation it is necessary to take into account two main econometric issues: the selection bias and the persistency of the R&D expenditure over time.

As regard to the first problem, Hall et al. (2009) point out that the selection bias is a potential issue when analyzing the determinants of R&D intensity. Indeed, firms' R&D behaviour can be described in terms of two equations: a selection

[3]Persistency in R&D expenditure is well documented by previous studies (Brown and Petersen (2011)). Our measure of R&D investment does not include staff costs which are usually looked at as the main source of persistency. Hence we expect to find a smallr coefficient on lagged R&D variable.

equation, that models the decision by the firm to perform R&D or not, and an intensity equation which explains the extent of R&D effort. In the literature, this representation is usually referred to Heckman selection model (Heckman, 1979). As pointed out by Baltagi (2005) the problem of self selection is worse in panels than in cross-sections. To correct for this kind of bias in a panel setting a widely adopted approach in the literature (Wooldridge, 1995; Jones and Labeaga, 2003; García et al., 2007) is to estimate the selection equation with a year-by-year probit model where the dependent variable is a dummy equal to 1 if the firm had a positive R&D expenditure in year t and 0 otherwise and, secondly, to insert the inverse Mills ratios, computed for each observation in each time period from the probit model, in the intensity equation, where the R&D expenditure is the dependent variable.

In addition, persistency is a well documented feature of R&D expenditure in the literature: due to the significant costs of adjusting R&D, larger than those for physical investment, firms should be more prone to maintain a smooth path of R&D investment over time (Hamermesh and Pfann, 1996; Brown and Petersen, 2011). The most adopted approaches in the literature to take into account this dynamic aspect are the estimators developed by Arellano and Bond (1991) and Blundell and Bond (1998), which overcome the endogeneity issue related to the inclusion of the lagged dependent variable (and other endogenous covariates) instrumenting endogenous variables with internal instruments (i.e. istruments based on lags of the instrumented variable). The Blundell and Bond system estimator (called System GMM) jointly estimates a regression in first differences with a regression in levels, using lagged levels as instruments for the regression in differences and lagged differences as instruments for the regression in levels. This methodology increases the efficiency of the produced estimates with respect to the Arellano and Bond estimator and it is preferable to a standard difference estimator since the inclusion of the lagged dependent variable in fixed effects model would lead to so-called Nickell (1981) bias, because the lagged dependent variable is correlated with the error term. Brown and Petersen (2011) choose the System GMM estimator to study R&D behaviour for a sample of U.S. firm, while Mulkay et al. (2000), in comparing R&D paths in U.S. and France, prefer the within estimator (whose bias is likely to become negligible as T increases)[4], to the GMM one, due to the weakness of their available instruments which tend to make the use of GMM very imprecise.

There is a limited number of studies, however, dealing at the same time with the dynamic panel dimension and selectivity (Jiménez-Martín, 2006; Jiménez-Martín

[4] See Nickell (1981) and Chamberlain (1982)

and Garcia, 2010; Lodigiani and Salomone, 2012). At our knowledge, this is the first attempt to put together the two aspects in describing R&D investment behaviour by firms. In order to do so, we employ a System GMM estimator after correcting for the selection bias using the Heckman strategy[5]. Basically, this means estimating T selection decisions using standard discrete choice model, computing the inverse Mills ratio for each observation and time period, and finally estimating both in levels and in first difference the intensity equation that includes the Mills ratio hereby calculated and where $R\&D_t$ and $R\&D_{t-1}$ is positive.

When employing System GMM estimator, a number of methodological choices have to be taken. The first issue is related to the selection of the potentially endogenous variables, the ones to instrument in addition to the lagged value of the dependent variable. The autoregressive formulation of R&D investment equation makes possible that also other firm's characteristics are correlated with past and current values of the idiosyncratic disturbances. For this reason, we include sales growth and expected sales growth as potentially endogenous , while age and the average number of employees are treated as exogenous. Since endogenous variables are instrumented with lagged values, it is also necessary to choose the number of lags to include into the instruments set: although the inclusion of an extra valid instrument should increase the asymptotic efficiency, even when it is weak, dropping those instruments that involve high-order lags, is a well established practice in applied works (see, for example, Kiviet, 2009; Roodman, 2009). We decide to use lagged levels dated from $t-2$ to $t-5$ as instruments for the regression in first differences and one lag of the difference as instrument for the level equation. We choose this set of instrumets also to avoid the problem of over-instrumenting.

We test the validity of the instruments chosen performing the standard tests proposed in the literature. First, we compute the test of over identifying restrictions proposed by Hansen, that coincides with the Sargan test in case of homoskedasticity, but represents a theoretically superior over-identification test in case of non sphericity in errors (see Roodman, 2009). This statistic is used to test whether the set of instruments is orthogonal to the error process, i.e. the exogeneity of the instrument. Moreover, we test the null hypothesis that the error term is not second orderly correlated, that would make lagged internal instruments correlated with the error term and GMM estimates inconsistent.

We perform two-step estimation on the ground that produce more efficient esti-

[5]In essence, the method is an extension of that proposed by Wooldridge (1995) to the dynamic case. The correction can be considered an approximation but has proved to work well in previous applications. See García et al. (2007).

mates than the one step and we apply the Windmeijer (2005) suggested correction, to fix the possible bias of the generated standard errors. Standard errors are also made robust to heteroskedasticity and to serial correlation.

Finally, we stress tha fact that we do not include sectoral and geographical dummies. As pointed out by Roodman (2009), it would be a mistake to include fixed effects in the level equation, since this implicit within transformation would invalidate the use of lags as internal instruments, violating the basic identification assumption of the model (exogeneity of the instruments).

5 Results

In implementing our estimation strategy, two steps need to be done. In the first step, the selection equation predicts the probability of reporting a positive R&D investment and this is estimated with a probit model. Generally, with respect to the intensity equation of the second step, an additional identification variable for the selection equation is inserted, even if, as pointed out in Wooldridge (2002), this is not strictly necessary. To this scope we use a dummy variable that captures if the firm exports or not its goods, since the degree of firm's openness to international trade is likely to influence the choice to do R&D while it is not presumably directly linked to the amount of R&D expenditure. Other regressors included that may affect the choice to perform R&D are the size (proxied by the average number of employees) and the age of the firm. Moreover, sectoral and geographical dummies are included. Table 5 displays the results of this first step estimations (one for each year of the sample, as explained in section 4).

In the second step the system GMM procedure is applied. Table 6 presents our baseline estimations, where our variables of interest – sales growth, expected sales growth and the forecasting error – are included subsequently. The inverse Mills ratio are always significant, confirming the presence of selection bias and hence the necessity to control for it. The negative coefficient can be interpreted as the existence of a negative correlation between the unobservable in the selection and the unobservable variables in the outcome equations. The lagged value of the share of R&D over total sales is significantly different from zero, and it is around 0.4, showing persistency in the levels of R&D investments[6]. In regression 1, the coefficient on the

[6]We have estimated equations (1)-(3) of Table 6 also employing the classical OLS estimator and the within-group one. Results, not shown here but available upon request, confirm the goodness of our estimates of the autoregressive coefficient on R&D expenditure. As pointed out by Bond (2002), this coeffient lies between the upper biased OLS estimate and the lower biased within-group

sales growth rate variable is not statistically different form zero, stating that R&D expenditures are neither pro-cyclical or countercyclical with respect to actual firm's business cycle. Explanatory power of observed business conditions appears to be very limited and this can be viewed as a black box hiding different effects within it. In order to properly catch the role of expectations, in the second column we substitute the actual value of sales growth with entrepeneurs' expectations about it: in this case the coefficient is significant and confirming the importance of expectations about the business cycle rather than business cycle evolution itself. Expected upturns in sales seem to push firms expanding the magnitude of R&D investments. The opposite hold in case of downturns. In particular an increase in expected sales growth of 1 percentage point makes grow R&D investment by 2.2 per cent. In column 3, in addition to expected sales, we add the forecast error. A large error can be related to the entrepreneurs' inability in predicting the future evolution of their business or to the occurrence of an unexpected shock. The coefficient found for the error term is not statistically significant. Firms that underestimated favourable changes will invest the same as firms whose forecasts exceeded the ex-post level of activity. This, again, confirms the central role of expectations: even if the entrepreneur observes a huge gap between predicted and realized sales during the year, she will not implement any adjustments in R&D to keep up with the changed environment[7].

Among firms' characteristics that may influence the R&D choices, age exerts a negative and significant influence, meaning that younger firms tend to invest more. The size of the firm, proxied by the number of employees, exerts a positive effects on the amount of R&D expenditure, as expected, since the dependent variable is the total amount of resources devoted to R&D. In all regressions, the standard tests for the instruments are reported at the bottom of the tables: the null hypothesis of exogenity of the instruments (Hansen test) and the null hypothesis of no second order serial correlation in errors (AR2 test) are always accepted.

After running regressions on the whole sample we have conducted a number of exercises splitting the sample according to firm characteristics that are more likely to drive firm's reaction to different expectations. We start from the age of the firm, dividing the sample according to the median of the sample distribution, which is equal to 33 years. Table 7 presents our results for young and old firms[8]. Observed

one.

[7]R&D characteristics behind its own persistency discussed above may contribute to explain the slow response by firms to perception of the changing environment.

[8]Also in this specifications we control for the age of the firm, since there is a huge variability within the two groups.

business cycle measures are not significant for both groups (first and third columns), while expectations turn out to be relevant in explaining R&D decisions for both. However for older firms the estimated coefficient is higher and more significant. This suggests that mature firms, benefiting of more experience on the markets, rely more on their expectations about the future than younger ones do and consequently react more promptly to expected changes.

Secondly, we split the sample according to the degree of uncertanty that characterizes the sector in which the firm operate. To measure the degree of uncertainty of a specific sector, we first compute, for each firm, the standard deviation of expected sales growth over the time span; then we take the average by sector (Table 8). High variability sectors include, on one side, the chemical, rubber and plastic industry and, on the other, the basic metals and engineering one, while low uncertain sectors are those typically caracterized by a more stable demand, such as food products, beverages and tobacco industry[9]. Again, as shown in table 9, observed business conditions do not seem to matter in explaining R&D expenditure, while expected conditions do. Estimated coefficients on expectations are higher for firms operating in more certaint sectors (columns 2 and 4). This result supports the view that when firms can reasonably believe in positive developments of their business tend to rely more on expectations and are more prone to increase their R&D investments in response to expected upturns. Firms operating in more uncertain environments tend to rely less on expectations and react in a milder way[10]. This result is relevant also from a policy point of view: macroeconomic policies, like a monetary one conducted by a credible central bank, aimed at creating a stable and more predictable economic environment allow firms making reliable plans and taking strategic decisions according to them. In addition, when designing policy packages to sustain innovation it is crucial to take into account the different sensitivity to expectations by firms belonging to different sectors. For example, if the economy perspectives are negative, firms in more volatile sectors are likely to respond less by cutting R&D investments, because they can't rely too much on what they foresee. As a result of this, the negative effect on the innovative effort will be quantitatively smaller than that of firms with the same forecast but operating in more stable sectors. If the

[9]We choose to compute the uncertainty in this way instead of taking the simple standard deviation of the expectations at sectoral level because in the latter approach also the residual sector (wood and other manifactures) would be classified as one with the highest variability. However, this is likely to be due to the heterogenous sectoral composition and to potentially different characteristics of firms belonging to it.

[10]This result is in line with the evidence in Guiso and Parigi (1999), who found that uncertainty weakens the response of investment to expected changes in demand.

objective of the policy is to increase R&D investment up to a certain threshold, hindering the effects of the recession, for example by offering a tax credit, it appears preferable to target directly the higher variability sector: the policy maker needs to exert smaller effort to obtain the same result.

To sum up, what emerges is that firstly entrepreneurial decisions depend mainly on expectations about the business cycle but not on the observed business cycle. Secondly, the perception of downturns tend to slow down innovative efforts by firms, while a positive attitude toward the future increases R&D investment. Thirdly, the lower the uncertainty in the economic environment, the higher the responsiveness of the investment to expected positive developments of the business.

6 Robustness checks

We perform several robustness checks related to the methodology chosen, to the definition of the dependent variable and to the set of controls in the regression (Table 10, 11 and 12).

A potential concern in our analysis is represented by our measure of R&D. In the Bank of Italy's Survey of Industrial and Service Firms, R&D expenditure reported by firms included advertisement and marketing expenses until the 2009 wave. From that moment on, only strictu sensu R&D expenditure is reported. Even if there is no evidence of a significant break in the series[11], we restricted our estimation sample to the period 2000-2009 in order to asses the validity of our results by using a coherently definition of the data (column 1 in Table 10): estimated coefficients are in line with those obtained using the full time span.

Apart from the controls related to the dependent variable, we perform additional robustness checks regards the econometric strategy. First, we show the results obtained without applying the Heckman correction and taking into account only positive R&D observations, as in Brown and Petersen, 2011 (column 2). Then, instead of the System GMM estimator, we apply the Arellano-Bond methodology that computes the coefficients using the model in differences (column 3 and 4, with and without the Hechman correction). In column 5 we report the baseline regression with the one step option for standard error, instead of the two step procedure. Arellano and Bond (1991) recommend using one step estimates for inference, because, when the sample size is small, standard errors of the two step GMM could

[11] A simple t-test does not show any difference in the two subsamples (before and after the change in the definition of R&D) in the average value of the R&D intensity, defined as the amount of R&D normalized by total sales.

be downward bias. Our results completely hold and, as in our baseline estimation, we find an increasing expenditure in R&D in case of expected upwards of the cycle. In table 11 we use different lags when choosing the instruments (in the baseline we choose the lags from $t-2$ to $t-5$). In column 1 we use lags form $t-2$ to $t-4$, in colum 2 from $t-2$ to $t-6$, and in column 3 we use the widest available set of instruments. As we can see, the choose of the lags form $t-2$ to $t-4$ is not enought to guarantee that the Hansen test is passed and this valorizes our choice of using also additional lags as instrument. However, in all the specifications the significance of the coeffcent on expectations is shown.

The last set of controls are related to the covariates included in the specification. First (in Table 11, columns 4, 5 and 6), we insert the lagged value of sales growth, to control if additional information about the past business cycle could be more informative than expections. Again, we find that the coeffcient for the observed conditions, both contemporaneous and lagged, are never statistically significant.

In table 12 we insert a number of financial variables typically associated by previous studies to firms' capacity to finance R&D expenditure (Aghion et al., 2012; see Ballatore et al., 2013, for a recent analysis of the relationship between ICT investments and financial factors). First of all, we add to our baseline specifications the cash flow generated by the firms in the previous year as an additional variable in order to control for the availability of internal funds to finance R&D expenditure (CF_{it-1}). As shown in columns 1 and 2, all our results hold robust, but the coefficient on cash flow is not significantly different from zero[12]. In columns 3 and 4 we add a firm-specific direct measure of credit restrictions ($rationed_{t-1}$), which makes it possible to distinguish between credit demand and credit supply factors. This is a dummy variable that takes value of one if the firm self reports to have been rationed in the credit market in $t-1$, as in Gaiotti (2013). In column 3 this variable is also interacted with sales growth, while in column 4 this is interacted with expected sales growth. No significant effects are found neither for the rationing dummy or for the interactions. This is likely to be due to the very low number of firms self reporting any rationing (around 4 per cent). To cope with this issue and to analyze the role of financial factors in a more nuanced way we finally insert another indicator of rationing: this is based on the probability of default which is computed annually by Cerved on balance sheet variables (the methodology is described by Altman, 1968 and Altman et al., 1994). This indicator takes values from 1 to 9 and is

[12]In all the specifications of Table 12, where additional financial variables are considered, the cash flow coefficients are never significantly different from zero.

increasing in the probability of default. In columns 5 and 6 we insert a dummy variable ($rating^{LOW}_{t-1}$) that takes value of one if the score is above 5, that identifies the weakest firms in financial terms, together with the two interaction terms with sales growth and expected sales growth as above. Again actual sales growth and the related interaction term with credit constraints do not display any significant effect on R&D expenditure. Interestingly in addition to the usual positive and significant effect of expectations in this case we find that the interaction between expectations and constraints show a negative and significant coefficient: a rationed firm invests less in R&D than a non rationed counterpart with the same expectation on the future. However the chi-squared test rejects the null hypothesis that the sum of the coefficients of expectations and of the interaction with the credit rationing variable is equal to zero. Thus, also R&D expenditure of credit rationed firms reacts positively to the expected business evolution, but to a lower extent with respect to firms with a better creditworthiness.

7 Conclusions

The impact of the economic cycle on the dynamics of R&D is a contentious issue in both the theoretical and the empirical literature. Although entrepreneurs' expectations for the future have been regarded as crucial determinants of investments at least since Keynes, investigation of their role has been limited by the lack of consistent time series at firm level. To our knowledge, this paper represents the first attempt to analyze the impact of firms' expectations on R&D expenditure. In order to do so, we applied a System GMM estimation strategy to a panel of Italian firms from 2000 to 2011, obtained by pooling different waves of the Bank of Italy's annual Survey of Industrial and Service Firms. In addition to the firm characteristics suggested by the recent literature, we explicitly introduce expectations of firms' business performance in place of observed conditions. Our results indicate that expectations of future demand are a crucial driver of R&D investments: firms base their R&D expenditure decision more on what they expect for the future than on what they observe in the present. In particular, they react to expected upturns in sales by increasing their innovative effort.

The impact of expectations on R&D decisions appears to be greater for older firms and for those operating in less volatile sectors. Consequently, policy action to stimulate R&D investments during the business cycle should take into account the different degree of sensitivity to expectations shown by firms belonging to different sectors or age groups. This work enriches the economic debate by shedding new light on firms' strategies during economic cycles. R&D appears to be a very forward-looking type of investment, one for which future prospects are crucial. Firms use R&D investments strategically during economic cycle to define their competitive position in accordance with their predictions and insofar as they can reasonably believe in the forecast.

References

Aghion, Philippe, and Gilles Saint-Paul (1998) 'Virtues of bad times interaction between productivity growth and economic fluctuations.' *Macroeconomic Dynamics* 2(03), 322–344

Aghion, Philippe, George-Marios Angeletos, Abhijit Banerjee, and Kalina Manova (2005) 'Volatility and growth: Credit constraints and productivity-enhancing investment.' NBER Working Papers 11349, National Bureau of Economic Research, Inc, May

Aghion, Philippe, Philippe Askenazy, Nicolas Berman, Gilbert Cette, and Laurent Eymard (2012) 'Credit constraints and the cyclicality of R&D investment: Evidence from France.' *Journal of the European Economic Association* 10(5), 1001–1024

Altman, Edward I. (1968) 'Financial ratios, discriminant analysis and the prediction of corporate bankruptcy.' *Journal of Finance* 23(4), 589–609

Altman, Edward I., Giancarlo Marco, and Franco Varetto (1994) 'Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience).' *Journal of Banking & Finance* 18(3), 505–529

Arellano, Manuel, and Stephen Bond (1991) 'Some tests of specification for panel data: Monte carlo evidence and an application to employment equations.' *Review of Economic Studies* 58(2), 277–97

Ballatore, Rosario M., Antonio M. Conti, Roberto Rassu, and Giuseppe Saporito (2013) 'Firms' innovation over the business cycle and the role of financial constraints. Evidence from ICT investments.' mimeo Bank of Italy, February

Baltagi, Badi H. (2005) *Econometric Analysis of Panel Data* (Wiley)

Barlevy, Gadi (2007) 'On the cyclicality of Research and Development.' *American Economic Review* 97(4), 1131–1164

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

Blundell, Richard, and Stephen Bond (1998) 'Initial conditions and moment restrictions in dynamic panel data models.' *Journal of Econometrics* 87(1), 115–143

Bond, Stephen R. (2002) 'Dynamic panel data models: a guide to micro data methods and practice.' *Portuguese Economic Journal* 1(2), 141–162

Brown, James R., and Bruce C. Petersen (2011) 'Cash holdings and R&D smoothing.' *Journal of Corporate Finance* 17(3), 694–709

Chamberlain, Gary (1982) 'Multivariate regression models for panel data.' *Journal of Econometrics* 18(1), 5–46

Comin, Diego, and Mark Gertler (2006) 'Medium-term business cycles.' *American Economic Review* 96(3), 523–551

D'Aurizio, Leandro, and Stefano Iezzi (2011) 'Investment forecasting with business survey data.' Temi di discussione (Economic working papers) 832, Bank of Italy, November

Durand, Rodolphe (2003) 'Predicting a firm's forecasting ability: The roles of organizational illusion of control and organizational attention.' *Strategic Management Journal* 24(9), pp. 821–838

Eisenhardt, Kathleen M., and Jeffrey A. Martin (2000) 'Dynamic capabilities: What are they?' *Strategic Management Journal* 21, 1105–1121

Gaiotti, Eugenio (2013) 'Credit availability and investment: Lessons from the "great recession".' *European Economic Review* 59, 212 – 227

García, Juan Ramón, Sergi Jiménez-Martín, and José María Labeaga (2007) 'Comparison of estimators in dynamic panel data sample selection and switching models.' Working Paper, June

Glaser, Markus, Philipp Schäfers, and Martin Weber (2007) 'Managerial optimism and corporate investment: Is the CEO alone responsible for the relation?' Working Paper 07-74, University of Mannheim, December

Griliches, Zvi (1990) 'Patent statistics as economic indicators: A survey.' *Journal of Economic Literature* 28(4), 1661–1707

Guiso, Luigi, and Giuseppe Parigi (1999) 'Investment and demand uncertainty.' *The Quarterly Journal of Economics* 114(1), 185–227

Hall, Bronwyn, Francesca Lotti, and Jacques Mairesse (2009) 'Innovation and productivity in SMEs: empirical evidence for Italy.' *Small Business Economics* 33(1), 13–33

Hamermesh, Daniel S., and Gerard A. Pfann (1996) 'Adjustment costs in factor demand.' *Journal of Economic Literature* 34(3), 1264–1292

Hartl, Jochen, and Roland Herrmann (2006) 'The role of business expectations for new product introductions: A panel analysis for the German food industry.' *Journal of Food Distribution Research*

Heckman, James J (1979) 'Sample selection bias as a specification error.' *Econometrica* 47(1), 153–61

Jiménez-Martín, Sergi (2006) 'Strike outcomes and wage settlements in Spain.' *LABOUR* 20(4), 673–698

Jiménez-Martín, Sergi, and Jaume Garcia (2010) 'Initial offers and outcomes in wage bargaining: Who wins?' *Empirical Economics* 39(3), 815–846

Jones, Andrew M., and José M. Labeaga (2003) 'Individual heterogeneity and censoring in panel data estimates of tobacco expenditure.' *Journal of Applied Econometrics* 18(2), 157–177

Kiviet, Jan F. (2009) 'Econometric analysis of panel data: Editorial introduction.' *The Singapore Economic Review* 54(03), 313–317

Lin, Yueh-hsiang, Shing-yang Hu, and Ming-shen Chen (2005) 'Managerial optimism and corporate investment: Some empirical evidence from Taiwan.' *Pacific-Basin Finance Journal* 13(5), 523–546

Lodigiani, Elisabetta, and Sara Salomone (2012) 'Migration-induced transfers of norms. the case of female political empowerment.' *DEGIT Conference Papers*

López-García, Paloma, José Manuel Montero, and Enrique Moral-Benito (2012) 'Business cycles and investment in intangibles: Evidence from Spanish firms.' Banco de Espana Working Papers 1219, Banco de Espana, May

Makadok, Richard, and Gordon Walker (2000) 'Identifying a distinctive competence: Forecasting ability in the money fund industry.' *Strategic Management Journal* 21(8), 853–864

Malmendier, Ulrike, and Geoffrey Tate (2005) 'CEO overconfidence and corporate investment.' *Journal of Finance* 60(6), 2661–2700

Mulkay, Benoit, Bronwyn H. Hall, and Jacques Mairesse (2000) 'Firm level investment and R&D in France and the United States: A comparison.' NBER Working Papers 8038, National Bureau of Economic Research, December

Nickell, Stephen J (1981) 'Biases in dynamic models with fixed effects.' *Econometrica* 49(6), 1417–26

Roodman, David (2009) 'How to do xtabond2: An introduction to difference and system GMM in Stata.' *Stata Journal* 9(1), 86–136

Windmeijer, Frank (2005) 'A finite sample correction for the variance of linear efficient two-step gmm estimators.' *Journal of Econometrics* 126(1), 25–51

Wooldridge, Jeffrey M. (1995) 'Selection corrections for panel data models under conditional mean independence assumptions.' *Journal of Econometrics* 68(1), 115–132

_ (2002) 'Inverse probability weighted m-estimators for sample selection, attrition, and stratification.' *Portuguese Economic Journal* 1(2), 117–139

Appendix

Table 1: Definition of variables

Variable name	Definition
$lnRD_t$	Natural logarithm of the R&D investment in t expressed in real terms
ΔS_t	Real sales growth rate in t
$E_{t-1}\Delta S_t$	Firm's expectation in $t-1$ for the real growth rate in t
err_t	Forecasting error. Difference between the realized value of real sales in t and the expectation made in $t-1$ for real sales in t : $err_t = \frac{S_t}{E_{t-1}(S_t)} - 1$, where $E_{t-1}(S_t)$ denotes the expectation made in $t-1$ for real sales in t and S_t denotes realized firm's real sales in t
$size_t$	Natural logarithm of the number of employees
age_t	Firm's age
CF_{t-1}	Firm's cash flow at time $t-1$, normalized by total assets.
$rationed_{t-1}$	Dummy variable equals 1 if a firm is credit rationed (source: Survey of Industrial and Service Firms).
$rating_{t-1}^{LOW}$	Dummy variable that identifies financial fragile firms, based on the Altman's indicator of the probability of default computed annualy by Cerved (Z-score indicator that ranges from 1, low risk, to 9, high risk). A firm is classified as financial fragile ($rating_{t-1}^{LOW} = 1$) if the Z-score is between 5 and 9.

All variables come from the Survey of Industrial and Service Firms, except for cashflow, derived from the Company Accounts Data Service data base.

Table 2: Summary statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
$lnRD_t$	3517	5.900	1.642	1.877	10.795
ΔS_t	3517	0.016	0.140	-0.554	0.658
$E_{t-1}\Delta S_t$	3517	0.035	0.096	-0.441	0.433
err_t	3517	-0.014	0.131	-0.656	1.579
$size_t$	3517	5.364	0.906	3.912	9.098
age_t	3517	40.213	27.011	1.000	190.000
CF_{t-1}	3140	0.049	0.046	-0.143	0.177
$rationed_{t-1}$	3466	0.043	0.204	0.000	1.000
$rating_{t-1}^{LOW}$	3242	0.370	0.483	0.000	1.000

All variables come from the Survey of Industrial and Service Firms, except for cashflow, derived from the Company Accounts Data Service data base.

Table 3: Correlations table

	$lnRD_t$	$lnRD_{t-1}$	ΔS_t	$E_{t-1}\Delta S_t$	err_t	$size_t$	age_t	CF_{t-1}	$rationed_{t-1}$	$rating^{LOW}_{t-1}$
$lnRD_t$	1.000									
$lnRD_{t-1}$	0.796***	1.000								
ΔS_t	-0.008	-0.019	1.000							
$E_{t-1}\Delta S_t$	0.023	0.002	0.461***	1.000						
err_t	-0.020	-0.022	0.713***	-0.189***	1.000					
$size_t$	0.495***	0.483***	-0.010	-0.016	0.010	1.000				
age_t	-0.013	-0.008	-0.007	-0.070***	0.038*	0.118***	1.000			
CF_{t-1}	-0.044*	-0.044*	0.033	-0.085***	0.083***	-0.031	-0.011	1.000		
$rationed_{t-1}$	-0.012	-0.010	-0.074***	0.019	-0.086***	-0.055**	-0.008	-0.119***	1.000	
$rating^{LOW}_{t-1}$	-0.037*	-0.027	-0.019	0.071***	-0.053**	-0.089***	-0.034	-0.474***	0.180***	1.000

Significance at 1% and 5% is denoted with *** and **, respectively.

Table 4: Average forecast error by year, sector and geographic area

(a) By year

Year	ΔS_t	$E_{t-1}\Delta S_t$	err_t	$abs\,(err_t)$
2000	0.069	0.048	0.024	0.084
2001	0.033	0.065	-0.023	0.096
2002	0.023	0.062	-0.031	0.093
2003	0.006	0.057	-0.043	0.100
2004	0.024	0.026	0.009	0.096
2005	0.042	0.068	-0.021	0.088
2006	0.048	0.022	0.029	0.091
2007	0.041	0.027	0.016	0.081
2008	-0.024	0.028	-0.051	0.093
2009	-0.129	-0.044	-0.088	0.129
2010	0.060	0.034	0.029	0.103
2011	0.025	0.030	-0.001	0.086
Total	0.016	0.035	-0.014	0.095

(b) By sector

Sector	ΔS_t	$E_{t-1}\Delta S_t$	err_t	$abs\,(err_t)$
Food products, beverages and tobacco	0.029	0.034	0.000	0.075
Texties, clothing, leather and footwear	0.008	0.026	-0.013	0.095
Chemical, rubber and plastic products	0.023	0.029	-0.002	0.078
Non-metallic minerals	-0.006	0.035	-0.035	0.096
Basic metals and engineering	0.022	0.040	-0.014	0.105
Other manufactures (wood, pulpand other)	0.000	0.030	-0.026	0.090
Total	0.016	0.035	-0.014	0.095

(c) By geographic area

Sector	ΔS_t	$E_{t-1}\Delta S_t$	err_t	$abs\,(err_t)$
North West	0.013	0.029	-0.014	0.092
North East	0.017	0.034	-0.012	0.089
Center	0.018	0.037	-0.012	0.097
South	0.015	0.044	-0.025	0.112
Total	0.016	0.035	-0.014	0.095

Table 5: Year-by-year probit estimation

	year2000	year2001	year2002	year2003	year2004	year2005	year2006	year2007	year2008	year2009	year2010	year2011
dRD												
$export_t$	0.667***	0.370***	0.635***	0.632***	0.707***	0.749***	0.731***	0.691***	0.535***	0.806***	0.770***	0.878***
	(0.153)	(0.123)	(0.122)	(0.128)	(0.135)	(0.134)	(0.139)	(0.129)	(0.127)	(0.138)	(0.144)	(0.159)
$size_t$	0.136**	0.149***	0.206***	0.286***	0.302***	0.276***	0.237***	0.207***	0.181***	0.194***	0.236***	0.165***
	(0.059)	(0.047)	(0.047)	(0.047)	(0.049)	(0.047)	(0.047)	(0.046)	(0.049)	(0.048)	(0.050)	(0.047)
age_t	0.000	-0.001	-0.001	0.002	0.001	0.001	0.001	-0.001	0.001	0.001	0.001	0.004**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Sectoral dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic area dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. Obs.	773	1083	1101	1114	1117	1141	1141	1171	1096	1116	1036	1058
pseudo R^2	0.080	0.046	0.075	0.108	0.104	0.106	0.090	0.076	0.090	0.091	0.107	0.135

Coefficients estimates and standard errors are reported in the table; standard errors are in parentheses. Significance at 1%, 5% and 10% is denoted with ***, ** and *, respectively.
The dependent variable (dRD) is a dummy equals to 1 if the firm signals a positive amount of R&D expenditures and to 0 if the firm does not invests in R&D.

Table 6: Baseline regressions

dependent variable: $lnRD_t$	(1)	(2)	(3)
$lnRD_{t-1}$	0.411***	0.410***	0.413***
	(0.055)	(0.061)	(0.059)
ΔS_t	0.253		
	(0.370)		
$E_{t-1}\Delta S_t$		2.216***	1.386**
		(0.756)	(0.542)
err_t			0.503
			(0.571)
$size_t$	0.473***	0.456***	0.483***
	(0.062)	(0.064)	(0.064)
age_t	-0.003***	-0.003**	-0.003***
	(0.001)	(0.001)	(0.001)
$Mills_t$	-0.682***	-0.793***	-0.680***
	(0.118)	(0.125)	(0.133)
N. Obs.	3517	3517	3517
N. Firms	1136	1136	1136
N. instruments	113	108	157
AR1[a]	0.000	0.000	0.000
AR2[a]	0.763	0.779	0.839
Hansen[a]	0.411	0.129	0.253

[a] p-value.

Two-step system GMM coefficients estimates and standard errors are reported in the table. Standard errors are robust to heteroskedasticity and with-in firm serial correlation (in parentheses). Yearly dummies are included in all regressions. Inverse Mills ratios ($Mills_t$) derived from year-by-year Probit.

Significance at 1%, 5% and 10% is denoted with ***, ** and *, respectively.

Table 7: Sample split between young and mature firms

dependent variable: $lnRD_t$	Young firms		Mature firms	
	(1)	(2)	(3)	(4)
$lnRD_{t-1}$	0.404***	0.472***	0.357***	0.290***
	(0.090)	(0.082)	(0.073)	(0.094)
ΔS_t	0.403		0.260	
	(0.551)		(0.433)	
$E_{t-1}\Delta S_t$		1.358*		2.003**
		(0.820)		(0.973)
$size_t$	0.473***	0.411***	0.609***	0.655***
	(0.097)	(0.091)	(0.083)	(0.110)
age_t	-0.018***	-0.015***	-0.001	-0.002
	(0.005)	(0.005)	(0.002)	(0.002)
$Mills_t$	-0.761***	-0.729***	-0.252	-0.436**
	(0.149)	(0.157)	(0.158)	(0.170)
N. Obs.	1605	1605	1799	1799
N. Firms	625	625	544	544
N. instruments	113	108	113	108
AR1[a]	0.001	0.001	0.000	0.000
AR2[a]	0.417	0.643	0.211	0.207
Hansen[a]	0.519	0.073	0.273	0.101

[a] p-value.
Two-step system GMM coefficients estimates and standard errors are reported in the table. Standard errors are robust to heteroskedasticity and with-in firm serial correlation (in parentheses). Yearly dummies are included in all regressions. Inverse Mills ratios ($Mills_t$) derived from year-by-year Probit.
Significance at 1%, 5% and 10% is denoted with ***, ** and *, respectively.

Table 8: Average standard deviation of expected sales growth by sector

Variable	*sd*
Food products, beverages and tobacco	0.0603
Texties, clothing, leather and footwear	0.0770
Chemical, rubber and plastic products	0.0777
Non-metallic minerals	0.0685
Basic metals and engineering	0.0892
Other manufactures (wood, pulpand other)	0.0701
Total	0.0793

Table 9: Sample split between sectors with low and high variability in growth rates of sales

dependent variable: $lnRD_t$	Low variability sectors		High variability sectors	
	(1)	(2)	(3)	(4)
$lnRD_{t-1}$	0.504***	0.436***	0.399***	0.403***
	(0.068)	(0.070)	(0.077)	(0.093)
ΔS_t	0.111		0.436	
	(0.572)		(0.349)	
$E_{t-1}\Delta S_t$		2.602**		1.638**
		(1.133)		(0.801)
$size_t$	0.321***	0.349***	0.586***	0.564***
	(0.077)	(0.073)	(0.093)	(0.105)
age_t	-0.001	-0.002	-0.004*	-0.003
	(0.001)	(0.001)	(0.002)	(0.002)
$Mills_t$	-0.431***	-0.646***	-0.381	-0.475**
	(0.151)	(0.180)	(0.232)	(0.219)
N. Obs.	1483	1483	2034	2034
N. Firms	486	486	650	650
N. instruments	113	108	113	108
AR1[a]	0.000	0.000	0.000	0.000
AR2[a]	0.630	0.695	0.995	0.981
Hansen[a]	0.180	0.362	0.429	0.321

[a] p-value.
Two-step system GMM coefficients estimates and standard errors are reported in the table. Standard errors are robust to heteroskedasticity and with-in firm serial correlation (in parentheses). Yearly dummies are included in all regressions. Inverse Mills ratios ($Mills_t$) derived from year-by-year Probit.
Significance at 1%, 5% and 10% is denoted with ***, ** and *, respectively.

Table 10: Robustness: baseline regression with different estimation tecniques

dependent variable: $lnRD_t$	Before 2009 (1)	Without sample selection (2)	Arellano Bond (1991) (3)	Arellano Bond (1991) No sample selection (4)	One step estimation (5)
$lnRD_{t-1}$	0.395***	0.390***	0.112*	0.107*	0.391***
	(0.069)	(0.061)	(0.064)	(0.065)	(0.057)
$E_{t-1}\Delta S_t$	1.985*	2.378***	1.347**	1.308*	2.162***
	(1.097)	(0.765)	(0.670)	(0.677)	(0.787)
$size_t$	0.481***	0.597***	-0.157	-0.077	0.475***
	(0.072)	(0.067)	(0.267)	(0.264)	(0.058)
age_t	-0.003**	-0.003**	-0.005	-0.005	-0.003***
	(0.001)	(0.001)	(0.005)	(0.005)	(0.001)
$Mills_t$	-0.759***		-0.542**		-0.710***
	(0.143)		(0.220)		(0.124)
N. Obs.	2936	3517	2073	2073	3517
N. Firms	1023	1136	669	669	1136
N. instr.	86	107	86	85	108
AR1[a]	0.000	0.000	0.000	0.000	0.000
AR2[a]	0.920	0.710	0.458	0.504	0.822
Hansen[a]	0.095	0.175	0.333	0.334	0.129

[a] p-value.

Eq. 1: Two-step system GMM estimation with inverse Mills ratios ($Mills_t$) derived from year-by-year Probit. Eq. 2: Two-step system GMM estimation. Eq. 3 and 4: Arellano and Bond (1991) GMM estimations, with and without inverse Mills ratios derived from year-by-year Probit. Eq. 5: One-step system GMM estimation with inverse Mills ratios derived from year-by-year Probit.

Standard errors are robust to heteroskedasticity and with-in firm serial correlation (in parentheses). Yearly dummies are included in all regressions.

Significance at 1%, 5% and 10% is denoted with ***, ** and *, respectively.

Table 11: Robustness: Baseline system GMM regressions with different sets of instruments and ΔS_{t-1}

dependent variable: $lnRD_t$	Different set of instruments			Baseline regressions with ΔS_{t-1}		
	Lag 2-4	Lag 2-6	Lag 2-∞			
	(1)	(2)	(3)	(4)	(5)	(6)
$lnRD_{t-1}$	0.417***	0.392***	0.399***	0.447***	0.477***	0.479***
	(0.059)	(0.061)	(0.063)	(0.059)	(0.060)	(0.061)
ΔS_t				-0.027		
				(0.296)		
$E_{t-1}\Delta S_t$	2.224***	2.149***	1.023*		1.316**	0.807*
	(0.848)	(0.774)	(0.559)		(0.530)	(0.463)
err_t						-0.112
						(0.425)
ΔS_{t-1}				0.100	0.162	0.071
				(0.137)	(0.145)	(0.136)
$size_t$	0.447***	0.472***	0.474***	0.429***	0.407***	0.409***
	(0.062)	(0.065)	(0.066)	(0.064)	(0.063)	(0.065)
age_t	-0.003**	-0.003**	-0.003***	-0.003**	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Mills_t$	-0.808***	-0.795***	-0.775***	-0.690***	-0.692***	-0.698***
	(0.124)	(0.125)	(0.131)	(0.117)	(0.119)	(0.124)
N. Obs.	3517	3517	3517	3426	3426	3426
N. Firms	1136	1136	1136	1117	1117	1117
N. instruments	93	121	157	148	153	202
AR1[a]	0.000	0.000	0.000	0.000	0.000	0.000
AR2[a]	0.772	0.808	0.842	0.684	0.699	0.725
Hansen[a]	0.066	0.225	0.366	0.578	0.309	0.562

[a] p-value.

Two-step system GMM coefficients estimates and standard errors are reported in the table. Standard errors are robust to heteroskedasticity and with-in firm serial correlation (in parentheses). Yearly dummies are included in all regressions. Inverse Mills ratios ($Mills_t$) derived from year-by-year Probit.

Significance at 1%, 5% and 10% is denoted with ***, ** and *, respectively.

Table 12: Robustness: The role of financial constraints

dependent variable: $lnRD_t$	Cash flow		Credit rationed firms		Firm's credit rating	
	(1)	(2)	(3)	(4)	(5)	(6)
$lnRD_{t-1}$	0.416***	0.417***	0.408***	0.419***	0.418***	0.400***
	(0.056)	(0.062)	(0.055)	(0.061)	(0.055)	(0.064)
ΔS_t	0.195		0.196		0.379	
	(0.380)		(0.383)		(0.458)	
$E_{t-1}\Delta S_t$		2.166***		2.159***		3.348**
		(0.738)		(0.769)		(1.321)
err_t						
$rationed_{t-1}$			0.010	0.030		
			(0.081)	(0.093)		
$\Delta S_t * rationed_{t-1}$			-0.562			
			(0.562)			
$E_{t-1}\Delta S_t * rationed_{t-1}$				-1.053		
				(0.905)		
$rating^{LOW}_{t-1}$					-0.024	0.075
					(0.056)	(0.075)
$\Delta S_t * rating^{LOW}_{t-1}$					-0.336	
					(0.444)	
$E_{t-1}\Delta S_t * rating^{LOW}_{t-1}$						-2.617**
						(1.269)
CF_{t-1}	-0.720	-0.194	-0.601	-0.125	-0.833	-0.343
	(0.531)	(0.588)	(0.535)	(0.593)	(0.588)	(0.622)
$size_t$	0.477***	0.464***	0.481***	0.467***	0.475***	0.473***
	(0.065)	(0.069)	(0.065)	(0.070)	(0.065)	(0.072)
age_t	-0.003**	-0.003*	-0.003**	-0.003*	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Mills_t$	-0.564***	-0.696***	-0.552***	-0.648***	-0.570***	-0.704***
	(0.121)	(0.120)	(0.123)	(0.118)	(0.118)	(0.120)
N. Obs.	3140	3140	3095	3095	3140	3140
N. Firms	1067	1067	1061	1061	1067	1067
N. instruments	114	109	116	111	116	111
AR1[a]	0.000	0.000	0.000	0.000	0.000	0.000
AR2[a]	0.528	0.567	0.607	0.681	0.502	0.692
Hansen[a]	0.486	0.199	0.480	0.262	0.478	0.234

[a] p-value.
Two-step system GMM coefficients estimates and standard errors are reported in the table. Standard errors are robust to heteroskedasticity and with-in firm serial correlation (in parentheses). Yearly dummies are included in all regressions. Inverse Mills ratios ($Mills_t$) derived from year-by-year Probit.
Significance at 1%, 5% and 10% is denoted with ***, ** and *, respectively.