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Published Version:
Investment–uncertainty relationship: differences between intangible and physical capital / Bontempi, Maria Elena. - In: ECONOMICS OF INNOVATION AND NEW TECHNOLOGY. - ISSN 1043-8599. - STAMPA. - 25:3(2016), pp. 240-268. [10.1080/10438599.2015.1076197]

Availability:
This version is available at: https://hdl.handle.net/11585/517792 since: 2020-04-06

Published:
DOI: http://doi.org/10.1080/10438599.2015.1076197

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Investment-uncertainty relationship: differences between intangible and physical capital

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Abstract

This paper disentangles the effects of uncertainty in explaining the heterogeneity of firms' investments. In particular, following Bloom (2007), we test the role of uncertainty and liquidity constraints extending the model to include R&D, non-R&D intangibles, as well as physical capital. The analysis is performed on a large dataset of Italian firms, covering both manufacturing and services sectors, as well as large and small firms. We show that non convex adjustment costs affect different capital inputs in different ways, depending on their degree of firm-specificity. The results confirm the Bloom model: flow adjustment costs explain investment in R&D and, to a lesser extent, in non-R&D intangibles. However, it struggles to explain tangible investment plans because of the ambiguous effect of the stock adjustment costs.

Keywords: investment; R&D; non-R&D intangibles; machinery; buildings; uncertainty; irreversibility; financial constraints; SMEs; panel data econometrics.

JEL: C3, C5, D22, D92, E22, E32, G32, L26, O3

1. Introduction

Investigating the role that uncertainty plays in investment is quite important at times, like the present one, of economic turbulence and reduced demand. In doing so, it is particularly important to pay attention to investment in intangibles, which are considered one of the main drivers of growth (Aghion and Howitt [2008]). See also the findings outlined by the OECD (2013).

In the last thirty years, the debate about the investment-uncertainty relationship has flourished, mainly in regard to tangibles, while little remains known about intangibles. Theoretical studies have struggled to come to any unequivocal conclusions about the sign and relevance of the investment-uncertainty relationship in the long-run, and the short-run effects appear to differ when comparing tangibles and intangibles.

Given the complex effects of uncertainty on investment, empirical evidence is of essential value. However, results are usually based on simulations, whereas very little evidence is based on micro data. This is mainly due to the difficulties in designing the degree of substitutability among inputs, the extent of irreversibility, of returns to scale and of market power. Moreover, the difficulty in finding convincing empirical counterparts to the concept of uncertainty is of even greater importance. Some results regarding tangibles are consistent with the negative predicted effects of real options, see Leahy and Whited (1996), Guiso and Parigi (1999), Bloom et al. (2007), Chirinko and Schaller (2009), Bontempi et al. (2010), Bianco et al. (2013). See also the reviews in Carruth et al. (2000) and Greasley and Madsen (2006).

Very few papers study the relationship between R&D expenses and uncertainty. Goel and Ram (2001) use nine OECD countries over the period 1981-1992, and find that uncertainty has a significantly negative effect on R&D, while it is not significant for non-R&D and aggregate investment (see also the extension in Drakos [2006]). Czarnitzki and Toole (2007, 2011, 2013) use different samples of "innovative" firms drawn from the German innovation survey of the manufacturing sector between 1995 and 2001. They find that product market uncertainty reduces R&D investment, and that this effect is smaller in markets where strategic competition is stiffer, and in the case of large firms; moreover, patent protection partially mitigates the influence of uncertainty. Stein and Stone (2012) analyse Compustat data for 3,965 US public companies over the period 2001-2011, and find that uncertainty depresses capital investment and advertising, but encourages R&D spending. "This perhaps surprising result for R&D is consistent with the theoretical literature emphasizing that long investment lags create valuable real put options which offset the effects of call options that are lost when projects are started." (Stein and Stone [2012], 1).

This paper analyses the peculiarities of investment in intangibles compared to investment in tangibles, with a specific focus on the effects of irreversibility, uncertainty and liquidity constraints. In doing so, we report for the first time, to our knowledge, empirical evidence regarding the theoretical model in Bloom (2007) for R&D, and we extend it to non-R&D intangibles, as well as to physical capital.

Thus a further novel aspect of our analysis is to compare the effects of uncertainty on different types of investments, since different capital inputs are known to be characterized by different degrees of irreversibility, which in turn is the main driver of the role of uncertainty in investment decisions. Drakos (2011) analyses buildings, machinery and equipment, and motors and vehicles for plant-level manufacturing data drawn from the Annual Industrial Survey for Greece (6,119 plants recorded over the 1993-2005 period); uncertainty has a negative effect on the extensive margin, decreasing the likelihood of triggering the investment in new capital. The analysis is taken one step further by Drakos and Goulas (2010) who analyze asset-specific and industry-specific irreversibility (measured in terms of the ratio of the average percentage of used capital to the sum of new and used capital expenditures). They show that uncertainty exerts a negative effect on total investment, as well as on investment in buildings, machinery and vehicles, while it exerts a positive effect on fixtures and fittings, in line with its lower degree of irreversibility. Driver et al. (2006) examine UK manufacturing industries and suggest that equipment expenditures are more ‘sunk’ than structures, and that structures are less specific in use and characterized by a lower degree of expandability (waiting to invest involves penalties); uncertainty has a negative effect on machinery investment, and a positive one on buildings.

Our analysis is based on an unbalanced panel of large and small/medium-sized enterprises in Italy, operating in both manufacturing and services sectors, observed over the 2003-2012 period. This data-set is interesting for many reasons. First, we dispose of a panel of survey data covering firms’ planned and completed investments of different types, expected future sales and demand uncertainty, and qualitative information about productive and financial conditions. This enables us to account for unobservable individual differences between firms, macroeconomic shocks and the evolution of the investment-uncertainty relationship. Secondly, Italy is a country characterized by limited economic growth over the last 10 years, compared to its international competitors and, in particular, to the nation’s past growth. Economic policy uncertainty may have exacerbated the doubts that firms face when deciding the amount and type of investment to be planned. Thirdly, the European accounting system allows for reporting as investments (i.e. to accumulate in assets) any spending on intangibles not directly related to current company operations, but representing the company's pledged resources designed to ensure future economic benefits (such as revenues or reduced future costs) (see Stolowy and Jeny-Cazavan [2001], and Bontempi and Mairesse [2014]).

The paper is organized as follows. Section 2 introduces the theoretical model of investment under the real option theory, and relates it to Bloom (2007). Section 3 lists alternative specifications of the empirical model for disaggregate investment assets. Section 4 reports the descriptive statistics of different types of investment and offers a preliminary examination of the data. Section 5 presents the estimates of investment models for R&D and for three other categories of capital goods, and assesses their robustness. Section 6 concludes. The Appendices respectively describe the data-set, define the variables in question, illustrate the additional features of R&D investment, and describe the dynamics of the Italian investment cycle.

2. Modelling the uncertainty-investment relationship: the theoretical underpinnings

When capital is characterized by an asymmetric adjustment-cost function, the initial cost of investment will not be recoverable once investment has been undertaken. Since investment is irreversible, the corresponding investment plan has a real option value reflecting the value that a firm places on its ability to choose the timing of its investment. Under highly uncertain demand conditions, the value of the option to postpone investment increases: it is convenient to wait for new information (Dixit and Pindyck [1994]), so that the decision to invest is delayed and current investment is curbed. The user cost of capital includes an irreversibility premium, and is positively affected by uncertainty about future demand conditions; positive investments are justified by higher threshold rates of return, and sunk costs create a zone of inaction - representing the option value of waiting - which is enlarged by greater uncertainty.

In order to compare the role of irreversibility and uncertainty in determining the investment behaviour of various types of capital input, we need a general model in which different effects are nested. In particular, since we want to compare tangible and intangible capital inputs, we base our analysis on the model proposed by Bloom (2007) for R&D. A generalization of the Bloom (2007) model can be written for period *t+1*, as:

$$r_{it+1} = \alpha_0 + \beta_1 r_{it} + \beta_2 \Delta y_{it+1} + \beta_3 \sigma_{it+1} + \beta_4 r_{it} \sigma_{it+1} + \beta_5 \Delta y_{it+1} \sigma_{it+1} + X_{it+1} + \varepsilon_{it+1} \tag{1}$$

where r is some measure of the investment ratio, y indicates the demand conditions (in logarithm), σ is *both individual and time variant* uncertainty about future business conditions, and X is a set of controls.

Uncertainty and irreversibility result in a rich short-term investment dynamics that may differ depending on the type of investment, due to the different nature of adjustment costs for tangibles and intangibles. Bloom (2007) suggests that while adjustment costs for physical capital arise directly from changing the stock (they are *stock* adjustment costs), adjustment costs for the stock of knowledge arise from changing the rate of change of accumulation (they are *flow* adjustment costs). This distinction leads Bloom (2007) to suggest investment over sales as a measure of r in the R&D case. While the investment ratio for tangibles is usually measured as investment over capital stock (see, e.g., Bloom et al. [2007]), a definition of the investment ratio such as the one proposed by Bloom (2007) is also suitable for other non-R&D intangibles, as well as for tangibles such as machinery or buildings. The distinction between adjustments in the level or growth rate of the stock also plays a crucial role in shaping the response of different investment types to uncertainty, as encapsulated by the three parameters β_3 , β_4 and β_5.

In both the tangible and intangible cases, increases in uncertainty have a direct negative effect on investment, since higher uncertainty leads firms to postpone their expenses, producing a negative "delay effect", represented by the β_3 parameter. According to Bernanke (1983), "In an environment in which the underlying stochastic structure is itself subject to random change, events whose long-run implications are uncertain can create an investment cycle by temporarily increasing the returns to waiting for information".

For both tangible and intangible capital inputs, uncertainty generates a "caution effect" in investment behaviour, represented by the negative β_5 parameter: in the short-run, firms' responses to demand shocks are lower at higher levels of uncertainty. A positive demand shock must be large enough to ensure that capital is moved up towards its investment threshold; even so, the investment response is lower than in the case of reversibility, since it is reduced by the zone of inaction.

What distinguishes tangibles from intangibles is the additional delay effect represented by the β_4 parameter. Unlike in the case of tangibles, Bloom (2007) suggests that the region of inaction creates a dynamic link between current and past R&D (or, we may presume, other intangibles) rates: if optimal R&D is higher than lagged R&D, and firms want to raise their spending (upward adjustment), then higher uncertainty will lead firms to postpone their investments, producing an "additional delay effect" regardless of whether the knowledge stock is decreasing or increasing. While for tangibles, lagged investment interaction with uncertainty might play no role in determining current investment under uncertainty[1], in the case of intangibles the impact of the

[1] The physical capital model of Bloom et al. (2007, 399) includes an error correction term with a supposed positive parameter, so that firms with capital stock below their target level will eventually adjust upwards. The target capital stock is the stock a firm would have chosen as a function of real sales and the user cost of capital. In other terms, in the long run it is the evolution of demand that drives investment, and not uncertainty and the gap between thresholds. Regardless of real options and irreversibility, uncertainty can only depress the expected long-term investment through its effect on the growth rate of demand (Bloom [2000]).

additional delay effect depends on the relationship between desired and lagged investment. This effect is encapsulated by a positive estimate of β_4 which takes into account the fact that uncertainty raises the response to lagged R&D expenditure, and the persistency of R&D investment.[2]

In Section 3 we will estimate different specifications of model (1) for both tangible and intangible rates. Together with expectations regarding the signs of the β_3, β_4 and β_5 parameters, we can also make predictions about their absolute values, which are presumed to be higher in the intangible case because of the causal link between adjustment costs and the degree of specificity of investment in intangibles. Intangible spending involves adjustment costs (Hall et al. [1986], Lach and Schankerman [1988]) and sunk costs (Bloom and Van Reenen [2002]) that are greater than those associated with tangibles. In fact, the output from investment in innovation displays a high degree of uncertainty, which is important at the beginning of a research program/project, when costs related to the need to employ skilled workers and to implement knowledge infrastructure are high. Moreover, many intangibles are highly firm-specific. In the words of Williamson (1988), intangibles are not "redeployable" assets, i.e. assets whose value when employed alternatively is almost as high as that of their current use.

Compared to physical capital, the lemon premium is particularly high for intangibles like R&D, because investors find it more difficult to distinguish good projects from bad ones. The result is that the market for R&D projects may entirely disappear if the asymmetric information problem is too large, and this "missing markets" problem leads to the irreversibility of R&D investment. If a company suffers from an idiosyncratic negative shock (firm-specific uncertainty), it will be unlikely to sell its research operations to another firm and get fairly good value for such, and so irreversibility is severe.

Furthermore, the equality between the marginal revenue product and the marginal cost of capital (the conditions for profits maximization) is affected by the peculiarities of intangibles. Some innovations can be cost-reducing; however, expensive marketing and advertising operations designed to promote the result of the innovation, are needed. Moreover, product enhancement and diversification mean that said product is not substitutable, and this will affect the elasticity of demand; hence, it is difficult to predict the effect on demand, and such effect may vary at different price levels.

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[2] Actually, the coefficient of the lagged dependent variable times uncertainty for physical capital is not obvious, as emerged in a private conversation with Nick Bloom: the gap between actual and desired investment ratios depends on lagged-uncertainty (how reluctant firms are to make adjustment vis-à-vis their recent past), while companies suffer from current uncertainty; these two effects will be related, but the sign is not clear. In other words, the response to uncertainty can be spread out over time, imparting complex and persistent dynamics; investment could respond to both current and past demand shocks, so that firms with a recent history of positive demand shocks will be closer to their investment threshold and will be more inclined to invest.

Finally, we should make one final important point regarding model (1): apart from the explicit Bloom (2007) determinants, any valid assessment of the impact of uncertainty on investment also requires financial variables as controls (in X_{it+1}). The reason for this is that a negative effect of uncertainty on investment might also proxy for credit constraints and/or agency costs: inherently riskier firms may find it more difficult to finance their spending and hence they may plan a lower level of investment. Furthermore, "to the extent that external finance - both through the debt and equity markets – is subject to agency and/or moral hazard problems, an increase in uncertainty will raise the user cost of capital, inducing a decline in investment spending" (Gilchrist et al. [2014] 1). The literature considers R&D investment (or, at a broader level, investment in intangible assets) as being more affected by financial constraints than investment in physical capital is (Himmelberg and Petersen [1994], Cincera [2003], Mulkay et al. [2001], Czarnitzki and Hottenrott [2011]). Moreover, the possibility of encountering financial constraints raises irreversibility (Holt [2007]). Hall and Lerner (2010) describe some of the unique characteristics of R&D investment that could explain why external funding of R&D might be more expensive than internal funding. Moreover, the value of any asset is contingent on the state of the world, and an asset may have a very different value to equity holders than to debt holders (Brynjolfsson and Hitt [2005]). Equity holders care about the expected returns of a firm and its assets across all future states of the world: intangibles are valuable for them as long as the firm is a going concern. Debt holders, on the contrary, care about what the firm would be worth in a bad global environment where it failed to generate sufficient cash flows to cover its required debt payment: from the debt holder's point of view, intangibles may even have zero value in such situations.

The financial variables we consider are cash flow and financial leverage. If we interpret model (1) as an adaptation of the first order condition of a discrete time value dynamic maximizing problem (the Euler equation approach derived in Bond and Meghir [1994]), the effect of cash flow is expected to be negative, as it depends on the magnitude of adjustment costs. A positive effect, on the contrary, indicates the agency costs of free cash flow (the overinvestment problem of Jensen [1986]) or an asymmetric information problem (the underinvestment problem of Myers and Majluf [1984]). The coefficient for financial debt should be not significant under the Modigliani-Miller debt irrelevance theorem, and significantly positive if there is no separability between investment and borrowing decisions as happens in imperfect capital markets where firms rely on debt, rather than on equity, for external financing (Whited [1992]). A negative value for debt is implied by bankruptcy costs and creditors'/shareholders' agency costs (Myers [1977]). High levels of debts could induce firms to opt for excessively risky investment projects (Jensen and Meckling [1976]), thus affecting the investment-uncertainty relationship; a negative investment debt relationship could be beneficial to shareholders of low-growth firms because banks can prevent their client firms from investing in unprofitable projects.

3. From the theoretical model to three alternative empirical specifications

The empirical implementation of model (1) can be accomplished through alternative specifications involving alternative measurements of the variables of interest. To organise the presentation, we start from model (2) for the generic capital input *j :*

$$\begin{aligned} R^j_{it+1} &= \beta_1 \frac{I^j_{it}}{Y_{it}} + \beta_2\ G_{it+1} + \beta_3\, U_{it+1} + \beta_4 \frac{I^j_{it}}{Y_{it}} \times U_{it+1} + \beta_5\ G_{it+1} \times U_{it+1} + \\ &+ \gamma_1 \frac{CF_{it}}{Y_{it}} + \gamma_2 \frac{D_{it}}{Y_{it}} + \mu_i + \tau_t + E^j_{it+1} \end{aligned} \tag{2}$$

The different empirical specifications we propose (in Table 1 below) are encapsulated by the proxy variables labelled R^j (for investment intensity, i.e. the ratio between investment in capital *j*, I^j, and sales, *Y*), *G* (for sales growth), and *U* (for uncertainty).

Besides the core relationship between investment intensity *R*, sales' growth *G* and uncertainty *U*, model (2) lists a number of control variables *X*: *CF* is the cash flow; *D* is the financial debt; μ_i and τ_t are the individual and time effects respectively, accounting for heterogeneity between and within firms[3], and *E* is the possibly heteroscedastic random error affecting investment intensity. Following the theoretical discussion in Section 2, we can make explicit predictions about the signs of the coefficients of model (2).The parameter $\beta_1 > 0$ is consistent with the positive residuals' serial correlation usually found in static models, and also gives a role to the "initial conditions" of actual investment when the new investment is set. The parameter $\beta_2 > 0$ shows that the investment activity is positively affected by sales growth. The parameters linked to uncertainty are: $\beta_3 < 0$ (uncertainty negatively affects investment intensity because it increases the value of waiting and seeing); $\beta_4 > 0$ (which indicates the additional delay effect i.e. the fact that in the presence of greater uncertainty, firms postpone investments and keep them closer to the initial conditions); $\beta_5 < 0$ (which represents the caution effect, i.e. the fact that under greater uncertainty, firms respond less to demand conditions). Finally, as far as the effects of

[3] Individual effects measure firm-specific irreversibility that can amplify the response of investment to uncertainty for a given capital good. Time effects account for panel cross-sectional correlation coming from individuals' reactions to macroeconomic events, neighbourhood/industry effects, herd behaviour and social norms.

financial control variables on investment intensity are concerned, we expect that: $\gamma_1 > 0$ indicates agency costs and asymmetric information problems, while $\gamma_2 > 0$ would suggest that companies prefer not to reveal information about their investment plans. These hypotheses seem appropriate in a bank-based system such as that of Italy (Bontempi [2002]).

The columns in Table 1 present the different specifications of model (2) according to alternative measures of the proxy variables *R*, *G* and *U*. We propose three empirical equations, respectively labelled as the "expectations model", the "plans-scaled model" and the "accounting-data model".

Table 1 here

The expectations model uses $\frac{{}_tI^j_{it+1}}{{}_tY_{it+1}}$ as the dependent variable *R* (i.e. the investment plans in *t* for period *t+1* over expected sales surveyed in *t* for *t+1*), and ${}_tg_{it+1}$ and $u({}_tg_{it+1})$ as the explanatory *G* and *U* (i.e. real sales' growth expected in *t* for *t+1*, and uncertainty about firms' future demand in *t* for *t+1*). In turn, $u({}_tg_{it+1})$ is defined as the difference between the maximum and the minimum expected real sales' growth in *t* for *t+1* (the so called subjective min-max range).

The plans-scaled model uses $\frac{{}_tI^j_{it+1}}{Y_{it}}$ as the dependent variable *R*, where plans are again in the numerator but Y_{it} , the level of actual sales known in *t* when the plan was made, is in the denominator. As in the expectations model case, explanatory *G* and *U* are measured by ${}_tg_{it+1}$ and $u({}_tg_{it+1})$. The accounting-data model uses $\frac{I^j_{it+1}}{Y_{it+1}}$ as the dependent variable *R*, so that both numerator and denominator are measured by actual accounting data. Explanatory demand conditions *G* are measured by actual sales' growth (g_{it+1}), and uncertainty *U* is measured either by the subjective min-max range above, $u({}_tg_{it+1})$, or by the disagreement, $se({}_tg_{it+1})$.[4] In the accounting-data model uncertainty measures are the only non-accounting information. Given that data on plans and expectations are usually not available, the accounting-data model (with some disagreement measure for uncertainty) is the most frequently used in the empirical literature, despite the fact that it disregards all information about individual expectations.

[4] The disagreement over expected growth rates of individuals by groups, $se({}_tg_{it+1})$, is estimated by the standard deviation of ${}_tg_{it+1}$ within groups of individuals.

The interpretation of the stochastic error E is model-specific: in both the expectations model and the plans-scaled model it represents the shock at time t when plans and expectations were formed, while in the accounting-data model it represents the shock from t to $t+1$, i.e. after plans and expectations were formed. Hence the accounting model error is a mix of many different macro- and micro-economic shocks.

The set of control variables, $X_{it+1} = \gamma_1 \frac{CF_{it}}{Y_{it}} + \gamma_2 \frac{D_{it}}{Y_{it}} + \mu_i + \tau_t$, is the same for all three specifications, and this is also true for the measure of initial conditions, given by the ratio between the actual investment in the j capital input of firm i at time t , I_{it}^j , over the actual sales' level„ Y_{it} . As a control variable in all three specifications, $\frac{I_{it}^j}{Y_{it}}$ might clean the residuals from autocorrelation due to e.g. adjustment costs and other rigidities. However, the interpretation of $\frac{I_{it}^j}{Y_{it}}$ is model-specific: in expectations and plans-scaled models, it is the actual investment intensity known at the time the plans are made (i.e. the initial conditions), while in the accounting-data model it is the genuine lagged dependent variable..

Although the three specifications are all reasonable empirical implementations of Bloom's (2007) theoretical model, they exploit different mixes of signal and noise. This is particularly relevant when the hypothesis of investment plan optimality is rejected, meaning that plans and realizations differ by more than the unpredictable noise that occurred after plans were made.[5] In a similar way, the measurement of the subjective uncertainty at firm-level and of the expected sales' growth disagreement within clusters can embody different amounts of information.[6] In general, alternative mixtures of information lead to different model estimates.

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[5] Given preliminary results available upon request, the outcomes of the tests for partial optimality with our data always reject the null of investment plans optimality, regardless of the alternative specification of the Mincer-Zarnowitz regression (proposed since the seminal work of Mincer and Zarnowitz [1969]). The discrepancy between plans and their actual realizations after one year is predictable at the time plans are made, and this suggests certain factors (such as bounded rationality or information asymmetries) that could negatively affect the planner's thinking. Consequently, investment plans and implementation do not bear the same information.

[6] Note that the subjective uncertainty $u({}_t g_{it+1})$, being firm- and time-specific, condenses the individual and time varying expectations of managers about future demand, and thus embodies those favourable features advocated in Manski (2004). Moreover, $u({}_t g_{it+1})$ is close to the definition given by Bloom et al (2007) of "uncertainty about demand and productivity conditions". In line with the findings of Lahiri and Sheng (2010), subjective uncertainty $u({}_t g_{it+1})$ and disagreement $se({}_t g_{it+1})$ markedly differ: our preliminary results - available upon request – from the comparison of these two uncertainty indicators call for great care in interpreting the outcomes of disagreement measures of variability, as they are prone to be extremely poor proxies, especially in the presence of an unstable economic environment (a case that, unfortunately, is often the rule rather than the exception).

Among the alternatives above, the investment planned for $t+1$ on the basis of the information in t, is the target variable that best encapsulates the effect of uncertainty on investment spending, due to three principal, interrelated reasons. Firstly, in the light of the Euler approach, we do not have to estimate the model by evaluating the expectation with their realized values and, in this way, we prevent the error term from embodying a miscellanea of shocks. Secondly, subjective uncertainty and expected sales growth provide information about firms' decisions, whereas when companies actually realize their plans in $t+1$, such information is – once again - mixed with the shocks that occur from t to $t+1$. Thirdly, plans are useful as they embody expected market conditions and discount the complexity of a particular project such as, for example, construction time (Kydland and Prescott [1982]) in the case of investment in buildings, or high adjustment costs in the case of R&D.

4. Data and preliminary analysis

Our data-set of company observations combines three sources: the Survey on Investment in Manufacturing (SIM), the Company Accounts Data Service (CADS), and the National Accounts data (NA). The last two offer additional information to that provided by the SIM. Details about the three data sources are set out in Appendix A1.

The main part of the data-set is drawn from the SIM, as it publishes both firms' expected demand and the uncertainty of such, as well as the effective and planned investments subdivided into four categories: (1) non-residential buildings (buildings, $j = f$); (2) machinery / equipment / vehicles (machinery, $j = m$); (3) software / licenses, permissions, concessions / intellectual property rights and trademarks / start-up expenses and other capitalized non-financial intangibles designed to improve productivity (non-R&D intangibles, $j = nr$); (4) research and development expenses (R&D, $j = r$). The four investment categories sum to the aggregate, labelled as $j = a$.

The CADS database includes highly disaggregated balance-sheet data (profit-and-loss and cash flow), as well as detailed information about the characteristics of Italian companies operating in a wide range of industrial and service sectors. The CADS covers about 72% of the SIM observations, and this is very important as this source supplements SIM information on financial variables.

Finally, NA data from the Italian National Institute of Statistics (ISTAT) provide additional information about time- and industry-specific deflators.[7]

The figures shown in the various columns of Table 2 allow for a preliminary assessment of the main features of the univariate distributions of the variables listed along the rows. In particular, the different rows refer to the following variables (detailed sources and definitions are in Appendix A2).[8]

The ratios ${}_tI^j_{it+1}/Y_{it}$ and I^j_{it+1}/Y_{it+1} are, respectively, planned investments and completed investments over actual sales in real terms; these two ratios respectively measure the dependent variable of the plans-scaled model and of the accounting-data model (see Table 1). The ratio ${}_tI^j_{it+1}/{}_tY_{it+1}$ (i.e. planned investments over planned sales in real terms) is also considered in order to assess how close the patterns of planned investments are, regardless of whether actual or planned real sales are contained in the denominator; this ratio measures the dependent variable in the expectations model (see Table 1). In Table 2 these variables are considered at both aggregate level, $j = a$, and by component, $j = m, f, nr,$ and r . Finally, ${}_tg_{it+1}$ is the expected growth rate of real sales between t and $t+1$, and $u({}_tg_{it+1})_{it}$ is the subjective uncertainty of firms regarding their demand in $t+1$ as perceived in t.

Table 2 here

All distributions in Table 2 are skewed to the right and mesokurtic (i.e. with means always larger than medians). This fact suggests long and fat right tails: a relatively small fraction of companies experience few, albeit large, investment episodes.[9] Apart from this common feature, all the other figures in Table 2 suggest that disaggregated capital goods show deep heterogeneity in their distributions across firms and over time (see also Bontempi et al. (2004)).

Among the categories of actual investments made, the highest coefficients of variation (corresponding to the lowest variability) are those of buildings and intangibles, while the use of investment plans reverses this outcome, as the highest coefficients of variation are those of tangibles. This last feature is robust to the use of expected sales as the scale variable for plans. In

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[7] Overall, the share of missing data in SIM covered by CADS information on financial variables is about 47%, while the share covered by NA information on deflators is about 29%.

[8] Besides the full sample analysis presented in this section, Appendix A3 - based on SIM surveys for 2010 and 2011 – also reports additional information on certain firms' characteristics and their R&D spending, and on the sources of R&D financing which are useful during the empirical modelling phase.

[9] Given that investment inaction followed by periods of intensive adjustment of capital stock may indicate a central role of non-convex (irreversibility) and of fixed adjustment costs that lead to lumpy investment (see e.g. Doms and Dunne [1998], Barnett and Sakellaris [1998], Cooper et al. [1999], and Cooper and Haltiwanger [2006]), Appendix A4 analyses the features of volatility, persistence and co-movements over time of investments at both macro- and micro-economic levels.

general, the fact that tangibles prevail over intangibles in the measures of dispersion, or vice versa, depends on the use of plans or of completions in the numerator of the investment ratio, and not on the use of actual or expected sales in the denominator.

The percentage of zero completed investments (column labelled as "Null obs." in Table 2) is particularly high for R&D, buildings, and Non-R&D intangibles. The same percentages computed for plans are ordered differently: first buildings, then non-R&D intangibles, and finally R&D. Again, the latter score is the same regardless of whether actual or expected sales are measured in the denominator of the investment ratios.[10] The average composition of investment spending in the ninth column of Table 2 suggests that machinery (j=*m*) is the most relevant investment category, followed by buildings and R&D (j= *f* and *r* respectively). The use of planned rather than actual data increases the relevance of R&D over total investment because of the smaller number of zeros in R&D plans than in actual R&D spending. As far as the sources of variability (between, over time and idiosyncratic-within) are concerned, the largest share of the overall variability of tangibles is explained by the idiosyncratic within component, while intangibles (Non-R&D and, mainly, R&D investments) vary more between (i.e. across firms) rather than over time within firms. This fact is robust to the measure - plans or completions - of investments.

As far as regards expected sales growth and uncertainty, i.e. the two main explanatory variables of the models summarised in Table 1, results suggest as follows. Uncertainty does not seem particularly affected by time variability, as between variability explains about 50% of total variability. Although expected sales growth displays the greatest time variability, its share remains below 4%. The coefficients of variation of subjective uncertainty and of expected growth are very different, as they are respectively the lowest (i.e. the highest dispersion) and one of the highest (i.e. the lowest dispersion) of those reported in Table 2.

The evidence emerging from our micro data can be cross-validated by comparing it with the benchmark evidence for the US, whose stylized facts have been introduced in Bloom (2007) as emblematic of his theoretical model for R&D. Table 3 reports the estimates of the second-order autocorrelation coefficients for the growth rates of sales and employees, and for the ratios of investment over sales, in Italy (using our micro data) and in the USA (using Compustat data).[11] To highlight the effect of zero R&D observations, we present coefficient estimates for Italy with and without zero R&D expenses.

Table 3 here

[10] Note also that the shares of observations with zero investments in tangibles (i.e. machinery and buildings) are quite close to those reported in Bloom et al. (2007) for the UK.

[11] The source of USA estimates is Bloom (2007), footnote 5 at page 252.

The second-order autocorrelation of sales' growth is very close to zero in both Italy and the USA, suggesting that they are generated by short-memory MA(1) processes (roughly the same result is given with regard to employment growth). The ranking of the estimates for both machinery and R&D is qualitatively the same in Italy and in the USA, with R&D being largely more persistent than machinery. In addition, the drop of null R&D expenses makes Italy even closer to the USA.

Overall, our results in Table 3 are so close to those in Bloom (2007) that we can describe the Italian case by quoting his words for the US case: "empirical evidence is that R&D rates change slowly over time, and are more persistent than sales growth, employment growth, or investment rates".[12]

5. Estimation results

As far as the econometric approach is concerned, even though expectations and plans-scaled models are not truly dynamic panel models,[13] shocks ε_{it} to investment plans are likely to be related to explanatory sales growth and uncertainty, as they are bound to interact in *t* with sales expectations and their range (i.e. uncertainty) formed for *t+1* (see notes *a* and *b* in Table 1). In addition, the endogeneity of the regressors can be further exacerbated by random measurement errors. Therefore, the identification process and consistent parameter estimation require instrumental variables for all three specifications.

The efficient GMM approaches of Arellano and Bond (1991), labelled as GMM-dif, and of Blundell and Bond (1998), labelled as GMM-sys, are appropriate estimators within our context. In the following, we support the choice of either GMM-dif or GMM-sys estimator by formally testing for the assumption of valid additional moment conditions used in the levels (the so-called Difference Hansen statistic, see e.g. Bond, 2002). Furthermore, the use of the two-steps GMM estimators, besides being the most efficient, also delivers consistent parameter standard errors in the presence of heteroscedastic and autocorrelated residuals.[14] Regarding the choice of instruments, we

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[12] For an extended analysis of the cyclical features of investments in Italy, see Appendix A4.

[13] In fact, the initial conditions regressor $\frac{I_{it}^{j}}{Y_{it}}$, being made of actual investments and actual sales, differs from the genuine lagged dependent variable of expectations and plans-scaled models, $\frac{{}_{t-1}I_{it}^{j}}{{}_{t-1}Y_{it}}$ and $\frac{{}_{t-1}I_{it}^{j}}{Y_{it-1}}$ respectively. The variable $\frac{I_{it}^{j}}{Y_{it}}$ represents a "true" lagged dependent variable in the accounting-data model only, and as such must be instrumented.

[14] Note that with our rather large sample sizes, the use of one-step GMM estimators or Windmeijer's finite-sample corrections to the asymptotic variance of the GMM estimators would deliver qualitatively similar results.

always use lags from *t-2* backwards of the explanatory variables, of disagreement, and of firms' indicators of belonging to a group and of being credit rationed.

The first three columns of Table 4 report the estimates of, respectively, the expectations, plans-scaled and accounting-data models (see Table 1) for R&D investments (i.e. $j=r$). In particular, the first two models are estimated with GMM-dif because the Difference Hansen test always rejects the over-identification conditions used in the levels; the opposite happens with the accounting-data model, where the GMM-sys estimator is preferred because both difference and level orthogonality conditions are not rejected by the Hansen test.

Table 4 here

Regarding the over-identifying restrictions tests reported in Table 4, the p-values of the Hansen test never reject the null of valid restrictions.[15] Models' residuals do not show any autocorrelation of the second-order or higher, suggesting that the shocks ε are independently distributed over time: as quite often happens, the initial conditions regressor $\frac{I_{it}^{j}}{Y_{it}}$ prevents residuals from autocorrelation due to adjustment costs and other rigidities. However, the very short average time dimension (about 2.3-2.4 years per firm) suggests cautious assessments of model dynamics. The explanatory ability of all the models is good, as the R^2 indicators are about 70% in models using plans and expectations, and just a little lower (about 50%) using noisier accounting data.

Estimates markedly differ for some key parameters, depending on whether model (2) variables are measured using plans/expectations or accounting data. In particular, the additional delay effect and the caution effect are relevant and right-signed (i.e. $\beta_4 > 0$ and $\beta_5 < 0$) in the two models explaining plans/expectations, while with accounting data, the delay effect β_4 is not significant and the caution effect β_5 is wrong-signed. In our view, these failures to support Bloom's predictions are related to the not significant estimate of the uncertainty parameter β_3 and to the significantly wrong sign of the estimate of the sales growth parameter β_2 . As expected, the use of actual rather than planned R&D investment can jeopardise the uncertainty effect, because the noise of too many sources of shocks hides the signal coming from subjective plans and expectations.

Regarding the wrong sign of β_2 when sales growth is measured using actual data, noisy demand shocks affecting sales growth data from t to $t+1$ can mechanically induce a negative correlation between the dependent variable (where the actual sales in $t+1$ are in the denominator) and the explanatory g_{it+1} . If the effect of sales growth on R&D plans is not very high (as suggested

[15] Note also that, being in the 20-35% range, these p-values are not too high to evoke a lack of power induced by too many over-identification restrictions; on this point see e.g. Bontempi and Mammi (2015).

by the two estimates of β_2 in the models using less noisy plans/expectations data), the negative correlation mentioned above can reverse the sign of the β_2 estimate in the accounting-data model.[16] In order to better understand this issue, we modified the accounting-data model specification by measuring its dependent variable with $\frac{I^r_{it+1}}{Y_{it}}$ instead of $\frac{I^r_{it+1}}{Y_{it+1}}$, and by changing both the lagged dependent variable, defined as $\frac{I^r_{it}}{Y_{it-1}}$, and the corresponding interaction term, defined as $\frac{I^r_{it}}{Y_{it-1}} \times u({}_t g_{it+1})$, accordingly. The GMM-sys estimate of β_2 in this modified accounting-data model, where the mechanical correlation described above is broken, goes from -0.023 (in the third column of Table 4) to a 10% significant 0.029 (close to the estimates from the plans/expectations models) and, while not significant, the estimate of β_5 is -0.042 rather than 0.093. This latter outcome, together with the β_5 estimates in the first two columns of Table 4 which clearly support the relevance of Bloom's caution effect, –underlines the need to use plans and expectations rather than accounting data to prevent potentially misleading shocks from giving signals that have little or nothing to do with the decision of investing in R&D.

Regarding the not significant estimate of the uncertainty parameter β_3 in the accounting-data model, we have to acknowledge that our subjective measure $u({}_t g_{it+1})$ is not very meaningful in this context, while it is so in the context of the plans/expectations models. Thus the failure to effectively represent the direct uncertainty effect β_3 in the third column of Table 4 precludes any appropriate assessment of either additional delay and caution effects, β_4 and β_5.[17] In fact, although the estimate of β_4 is within the range of those estimates obtained using the plans/expectations data in the first two columns, the volatility of the β_4 estimator with accounting data prevents its statistical significance; the same occurs in the case of the β_5 estimates of the modified accounting-data model described above. Therefore, models using plans and expectations data embody the best information, and call into question the use of the accounting-data model in assessing the effect of uncertainty on

[16] Define, in the plans-scaled model, the change in R&D spending I^r over the lagged level of sales Y due to a change in the sales growth rate g as $\beta_2^S = \partial \frac{I^r_{it+1}}{Y_{it}} \Big/ \partial g_{it+1}$. The corresponding β_2 parameter in expectations and accounting-data models is related to β_2^S by means of the following formula: $\beta_2 = \frac{\beta_2^S - I^r_{it+1}/Y_{it}}{1+g_{it+1}}$. Therefore, given a positive estimate of β_2^S, the precondition for a positive estimate of β_2 as well is that: $\hat{\beta}_2^S > \frac{I^r_{it+1}}{Y_{it+1}}$.

[17] Note that qualitatively similar results are obtained if we measure uncertainty with disagreement rather than with the subjective min-max range.

investment. Similar evidence, in the case of tangibles, is reported in Guiso and Parigi (1999), and in Bontempi et al. (2010).

The outcomes in the first two columns of Table 4 clearly support Bloom's model, even though comparisons between specific parameter estimates of the expectations model (in the first column) and the plans-scaled model (in the second column) require further explanation.

First of all, in view of the foregoing discussion, it is not surprising that estimates of the expected demand growth effect β_2 markedly differ, and that the smallest estimate (0.010) derives from the expectations model. In fact, this latter estimate - besides being inversely related to the level of expected growth - is also a function of the difference between the plans-scaled model estimate (0.028) and the share of R&D on sales levels (which can be seen from the formula in footnote 16). In other words, the β_2 estimate of the expectations model is lower than that of the plans-scaled model by an amount related to the R&D/sales ratio (the larger this ratio, the larger the difference between the two estimates). This feature suggests that the specification based on plans-scaled model is probably better, from a statistical point of view, than that based on the expectations model: the latter model estimates a β_2 parameter which is related not only to the elasticity of plans to expected sales growth, but also to the R&D/sales ratio which can strongly vary across firms. The estimates of the caution effect β_5 are almost equal in the two models (while those of β_2 are quite different); thus, we can predict that an equal increase in uncertainty will offset the effect of a positive demand shock to a greater extent in the case of the expectations model than in that of the plans-scaled model.

The estimates of the direct uncertainty effect β_3 are quite similar in the two models, and emphasise the negative effect on R&D plans due to an increase in uncertainty. If we measured the uncertainty with disagreement, rather than the subjective min-max range, the results of the estimation would change quite substantially (available upon request): the estimate of expected sales growth β_2 would become negative (from positive), and - accordingly - the sign of the estimate of the caution effect β_5 would become positive. The instability of the economic environment over the estimation sample makes uncertainty measured as disagreement to behave quite differently from uncertainty measured from the subjective expectations of managers (see Lahiri and Sheng [2010]), and this discrepancy is likely to prevent those models using disagreement from encapsulating genuine uncertainty shocks.[18]

[18] In order to investigate this point further, we estimated the expectations model using both subjective uncertainty and - alternatively - disagreement in two sub-samples (before and after 2008) characterized by different degrees of stability in the economic environment. Results (available upon request) are quite clear cut: while the estimation results of the model using subjective uncertainty show a remarkable stability across the sub-samples, those deriving from the model using disagreement show profound parameter breaks in the estimates of delay and caution effects β_4 and β_5. The cyclical instability of the latter model emphasizes the problems occurring when the economic environment is unstable.

The estimates of the initial conditions' effect β_1 are similar in both the expectations and plans-scaled models, and denote the relevance thereof: more than 80% of investment plans for the following year are, *ceteris paribus*, in line with what happened during the previous period. In particular, firms confidently forecasting zero growth for their next year's sales, will plan on spending only a slightly lower amount on R&D than the amount spent the previous year. On the contrary, the estimates of the delay effect β_4 markedly differ, being significantly lower in the expectations model. This discrepancy is puzzling, because classical GMM diagnostics do not show any significant signs of any specification problems. A tentative interpretation could be based on the large shocks – and uncertainty – that characterised the Great Recession, when the dynamic relationship between plans and actual investment could have been prone to be characterized by outliers and non-linearity; these effects are particularly difficult to identify within the short period in which they occurred.

Since GMM-dif estimators can be biased towards OLS-in-differences estimates in dynamic models with a high degree of persistence, and GMM-sys are biased towards the OLS-pooled estimates when initial conditions are related to the individual effects (see Blundell and Bond [1998] and Bond [2002]), the last two columns of Table 4 report the OLS-pooled and the OLS-in-differences estimates of the expectations model parameters, respectively.[19] As far as the estimates of inertia effect β_1 are concerned, they suggest that the bias of the GMM-dif estimator is not too strong, as the β_1 estimate lies between the upwardly-biased OLS-pooled and the downwardly-biased OLS-in-differences estimates. Under OLS-pooled, the omission of the individual effects, possibly positively correlated with the explanatory uncertainty, would upwardly bias the estimate of the β_3 parameter and, accordingly, downwardly bias the estimate of the caution effect β_5. Estimates in the fourth column of Table 4 confirm this prediction, as both β_3 and β_5 signs are significantly wrong. This evidence is further validated by inspecting the corresponding estimates with OLS-in-differences in the fifth column, where the first-difference transformation clears individual effects: albeit not significant, the estimate of the uncertainty effect becomes negative and that of the caution effect is in line with the GMM estimates.

The vertical axis in the upper part of Figure 1 measures a dynamic delay effect, equal to $\beta_1 + \beta_4\, u({}_t g_{it+1})$, which grows with uncertainty (measured along the horizontal axis) because the estimate of β_4 in the plans-scaled model is equal to about 0.53 (see the second column of Table 4). For example, when uncertainty is at very low levels (1% corresponds to the 5th centile of its sample

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[19] What is discussed here also holds true qualitatively for the unreported OLS estimates of the plans-scaled and the accounting-data models.

distribution), the delay effect is about 0.87 (which is very close to the estimate of β_1 in the plans-scaled model); this means that the delay effect leads to planned R&D investment for the following year that is about 87% of the R&D investment made this year. Instead, when uncertainty is very high (25% corresponds to the 95th centile of its sample distribution), the delay effect is about 1; this means that the delay effect leads to planned R&D investment for the next year that is equal to the R&D investment made this year. In other words, the grey upper area of the delay effect gets larger as uncertainty grows.

Figure 1 here

The lower vertical axis measures a caution effect, equal to $\beta_2 + \beta_5\ u({}_tg_{it+1})$, which decreases with uncertainty because the estimate of β_5 in the plans-scaled model is equal to about -0.12. For very low levels of uncertainty, the caution effect is about 0.028 (which is very close to the estimate of β_2 in the plans-scaled model), while for very high levels of uncertainty, the caution effect is about 0; this means that due to caution effects, R&D investment plans for the following year are unrelated to the level of growth in demand expected for that year. In other words, the lower grey area of the caution effect gets larger with uncertainty.

In order to cross-validate the ability of Bloom's model for R&D to explain other investment decisions as well, Table 5 compares the estimates of the plans-scaled model with R&D data (in the first column), with those corresponding to other investment categories (in the other four columns), namely: total, equipment, buildings and Non-R&D intangibles. Model diagnostics suggest the plans-scaled model is also statistically congruent with non R&D investment data.

Table 5 here

Some results in Table 5 support the caution effects model, and the findings are quite robust across investment type: the sales growth parameter estimates are always significantly positive, and their interaction with uncertainty is almost always negative (with the exception of buildings, which also score the lowest reactivity - among tangibles - to expected demand *one*-year ahead). On the other hand, the findings regarding the delay effect β_4 are mixed, as non-R&D intangibles are the only case (besides R&D) in which Bloom's theoretical *a priori* is met. This outcome is consistent with Bloom's assumptions: higher uncertainty increases the responsiveness of investment to lagged investment as predicted by flow adjustment costs for intangibles (both R&D and Non-R&D).[20] Since, vice-versa, in the cases of capital and labour the most reasonable assumption is that of stock

[20] In particular, for Non-R&D intangibles we have the extreme case in which the delay effect only comes about as a result of the interaction with uncertainty, as the estimate of β_1 is not significant while that of β_4 is both significant and very large.

adjustment costs, there is no reason to expect the delay effect to actually materialize for tangibles, where one would rather expect the delay effect at the stock level, not at the flow (investment) level. Therefore, in the context of Bloom (2007), β_4 parameter for capital goods should be negative, and its estimates in Table 5 are actually negative for machinery, buildings and the aggregate estimates.

As regards the effects of financial variables, overall such effects are significant, regardless of whether the expectations or the plans-scaled model is used (see Table 4), and regardless of alternative investment assets (see Table 5). The prevalence of significantly positive cash flow effect estimates suggests the presence of agency costs and asymmetric information. The positive relationship with debt in the case of intangibles seems to underline the role of borrowing in reducing those company resources freely available to managers (Panousi and Papanikolaou [2012]). Note also that bank debt is the main source of financing in Italy, and its use can prevent companies from revealing information (such as that regarding R&D projects) to a large number of investors. See Bontempi (2002) and Munari et al. (2010) for comparative analyses of R&D investment in control-based systems (such as Italy).

6. Concluding remarks

In this paper we study the empirical determinants of R&D investment by implementing for the first time (to the best of our knowledge) the theoretical model introduced in Bloom (2007). The Italian case is interesting as it offers a wealth of firm-level data, i.e. disaggregated investment plans and their implementation, as well as a subjective firm- and time-varying measure of expected demand and the uncertainty thereof. Even though Bloom's model has been specifically designed to explain the effect of uncertainty on R&D investment, here the model is also applied to four types of capital goods: two types are tangible (buildings and machinery-equipment) while two are intangible (R&D and Non-R&D intangibles). This comparison is rather relevant, since different types of capital can be differently affected by areas of inaction due to irreversibility, fixed adjustment costs, asymmetric information and financial constraints.

In modelling data, a number of issues concerning the measurement of the variables in question, and the other specifications, are tackled. Our main findings can be summed up as follows. Given that the discrepancy between investment plans and their corresponding implementation is not simply due to unforecastable random errors occurring after the plans are made, the decision to estimate the model by using either investment plans or completed investments (and, accordingly, by using either sales expectations or their ex post accounting outcomes) leads to different results. The same is true regarding the alteration of the definition of uncertainty, i.e. the use of either the subjective range of expected sales growth or the disagreement between individual expectations within individual economic sectors.

As shown within the context of tangible goods (see Guiso and Parigi, 1999, and Bontempi et al., 2010), also in the case of R&D, investment plans, sales expectations and their subjective uncertainty (min-max range) measure the theoretical determinants of firms' behaviour to a better degree than actual *ex post* data do, as the latter are affected by additional noisy shocks not necessarily related with the issue in question. Therefore, the significant estimates we found for Bloom's model determinants support the existence of flow adjustment costs for intangibles, while the partial failure to identify valid empirical representations for tangibles suggest that, as assumed in the theoretical framework, they are subject to stock adjustment costs. Therefore, our estimation results for investment in physical capital support the empirical specification of Bloom et al. (2007) and of Drakos and Goulas (2010), whereby uncertainty only comes into the equation through its interaction with demand and/or directly.

As regards R&D investment, the response of companies to demand shocks is significantly lower at higher levels of uncertainty because of a caution effect: the chance to wait and do nothing is more valuable for those firms that encounter a higher level of demand uncertainty. Following a negative demand shock, investment is expected to be lower, as each firm will invest less (the so-called intensive margin). According to our data, very high levels of uncertainty may completely displace positive demand shocks, and for this reason lead firms to totally rely on their existing investment-sales ratios. Therefore, the main relevance of this work for policy purposes is that it shows how uncertainty delays R&D investment, and this fact implies that nowadays, R&D spending may be strongly penalized in countries like Italy, where the level of uncertainty is currently rather high.

Acknowledgement

This paper is part of a general research project concerning the relationships between investment and uncertainty at both micro and macro levels, conducted jointly with Magda Bianco and Giuseppe Parigi (Bank of Italy), Cecilia Jona-Lasinio and Fabio Bacchini (ISTAT), Jacques Mairesse (ENSAE), and Roberto Golinelli from my own Department; see Bontempi et al (2010), Bianco et al. (2013), Bontempi and Mairesse (2014), and Bacchini et al. (2015). I would like to thank these colleagues not only for their comments and encouragement, but also for allowing me to use our procedures and data. A preliminary version of this paper was presented at the 4th European Conference on Corporate R&D and Innovation: "Financing R&D and innovation for corporate growth in the EU: Strategies, drivers and barriers" (CONCORDi-2013), European Commission, JRC-IPTS, Seville, Spain. My thanks also go to Nick Bloom, Bronwyn Hall and Werner Hölzl, to four anonymous reviewers, and to conference participants for their comments. The usual caveats apply. Elisa and Ernesto, thank you for being so marvellous.

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Tab. 1 – Summary of the three empirical models

	Specification		
Proxies in equation (2):	**Expectations model** [a]	**Plans-scaled model** [b]	**Accounting model** [c]
R (investment intensity)	Planned investment /Expected sales	Planned investment /Actual sales lagged	Actual investment /Actual sales
G (sales' growth rate)	Expected sales growth	Expected sales growth	Actual sales growth
U (uncertainty)	Min-Max range of sales growth expectations	Min-Max range of sales growth expectations	Min-Max range of sales growth expectations OR disagreement among firms in the industry

([a]) $$\frac{{}_tI^j_{it+1}}{{}_tY_{it+1}} = \beta_1 \frac{I^j_{it}}{Y_{it}} + \beta_2\, {}_tg_{it+1} + \beta_3\, u({}_tg_{it+1}) + \beta_4 \frac{I^j_{it}}{Y_{it}} \times u({}_tg_{it+1}) + \beta_5\, {}_tg_{it+1} \times u({}_tg_{it+1}) + \gamma_1 \frac{CF_{it}}{Y_{it}} + \gamma_2 \frac{D_{it}}{Y_{it}} + \mu_i + \tau_t + \varepsilon_{it}$$

([b]) $$\frac{{}_tI^j_{it+1}}{Y_{it}} = \beta_1 \frac{I^j_{it}}{Y_{it}} + \beta_2\, {}_tg_{it+1} + \beta_3\, u({}_tg_{it+1}) + \beta_4 \frac{I^j_{it}}{Y_{it}} \times u({}_tg_{it+1}) + \beta_5\, {}_tg_{it+1} \times u({}_tg_{it+1}) + \gamma_1 \frac{CF_{it}}{Y_{it}} + \gamma_2 \frac{D_{it}}{Y_{it}} + \mu_i + \tau_t + \varepsilon_{it}$$

([c]) $$\frac{I^j_{it+1}}{Y_{it+1}} = \beta_1 \frac{I^j_{it}}{Y_{it}} + \beta_2 g_{it+1} + \beta_3\, u({}_tg_{it+1}) + \beta_4 \frac{I^j_{it}}{Y_{it}} \times u({}_tg_{it+1}) + \beta_5 g_{it+1} \times u({}_tg_{it+1}) + \gamma_1 \frac{CF_{it}}{Y_{it}} + \gamma_2 \frac{D_{it}}{Y_{it}} + \mu_i + \tau_t + \varepsilon_{it+1}$$

OR

$$\frac{I^j_{it+1}}{Y_{it+1}} = \beta_1 \frac{I^j_{it}}{Y_{it}} + \beta_2 g_{it+1} + \beta_3\, se({}_tg_{it+1}) + \beta_4 \frac{I^j_{it}}{Y_{it}} \times se({}_tg_{it+1}) + \beta_5 g_{it+1} \times se({}_tg_{it+1}) + \gamma_1 \frac{CF_{it}}{Y_{it}} + \gamma_2 \frac{D_{it}}{Y_{it}} + \mu_i + \tau_t + \varepsilon_{it+1}$$

Tab. 2 – Descriptive statistics of the main variables [(a)]

	Median	Mean	SD /Mean	IQR	SD	SD be	SD td	SD re	$\frac{I_{it}^{j}}{\sum_j I_{it}^{j}}$	Null obs.	Total # obs.
Variables [(b)]						% [(c)]	% [(c)]	% [(c)]	%	%	
${}_tI_{it+1}^{a}/Y_{it}$	0.025	0.062	15.242	0.047	0.945	21.33	0.10	78.57	100	4.0	16425
${}_tI_{it+1}^{m}/Y_{it}$	0.012	0.044	10.682	0.030	0.470	20.20	0.09	79.71	66.4	15.6	39595
${}_tI_{it+1}^{f}/Y_{it}$	0.000	0.013	16.846	0.002	0.219	21.83	0.08	78.09	11.1	64.9	39595
${}_tI_{it+1}^{nr}/Y_{it}$	0.000	0.003	10.333	0.002	0.031	49.30	0.05	50.65	7.2	41.6	39057
${}_tI_{it+1}^{r}/Y_{it}$	0.000	0.009	4.111	0.005	0.037	82.72	0.03	17.25	15.4	25.0	16748
I_{it+1}^{a}/Y_{it+1}	0.024	0.064	4.156	0.049	0.266	43.09	0.19	56.72	100	5.0	33265
I_{it+1}^{m}/Y_{it+1}	0.014	0.044	5.636	0.031	0.248	36.17	0.11	63.72	69.8	10.6	39075
I_{it+1}^{f}/Y_{it+1}	0.000	0.015	16.200	0.004	0.243	21.03	0.07	78.90	14.0	56.1	39075
I_{it+1}^{nr}/Y_{it+1}	0.000	0.003	14.333	0.002	0.043	69.79	0.03	30.18	7.3	38.8	39057
I_{it+1}^{r}/Y_{it+1}	0.000	0.006	5.167	0.000	0.031	63.36	0.04	36.60	9.0	63.4	33981
${}_tI_{it+1}^{a}/{}_tY_{it+1}$	0.025	0.058	16.052	0.045	0.931	26.71	0.09	73.20		3.3	14492
${}_tI_{it+1}^{m}/{}_tY_{it+1}$	0.013	0.038	13.105	0.028	0.498	29.02	0.07	70.91		9.3	25431
${}_tI_{it+1}^{f}/{}_tY_{it+1}$	0.000	0.011	21.545	0.002	0.237	34.32	0.06	65.62		41.1	25431
${}_tI_{it+1}^{nr}/{}_tY_{it+1}$	0.000	0.002	6.500	0.002	0.013	56.42	0.02	43.56		25.3	25024
${}_tI_{it+1}^{r}/{}_tY_{it+1}$	0.000	0.008	3.625	0.005	0.029	74.85	0.08	25.07		21.9	14767
${}_tg_{it+1}$	0.008	0.012	12.324	0.094	0.148	38.31	3.55	58.14			25444
$u({}_tg_{it+1})$	0.060	0.090	1.028	0.070	0.092	51.76	0.92	47.32			13907

([a]) Survey data available for t = 2003, 2004, ..., 2011.
([b]) Disaggregation: $j = m$ (machinery, equipment, vehicles), f (buildings), nr (non-R&D intangibles), r (R&D), a (aggregate, i.e. the sum of the previous four categories. ${}_tI_{it+1}^{j}$ and I_{it+1}^{j} are respectively planned and realized investments in each category j; Y_{it} and ${}_tY_{it+1}$ are respectively actual sales in t and expected sales in t for $t+1$; ${}_tg_{it+1}$ is the expected rate of growth of sales in t for $t+1$; $u({}_tg_{it+1})$ is uncertainty about future sales as perceived in t for $t+1$.
([c]) Total standard deviation, *SD,* is decomposed in three % shares by using the appropriate sums of squared deviations: the time-invariant firm-specific component (between firms, *SDbe*, based on $T_i\sum_{i=1}^{N}(y_{i.}-y_{..})^2$); the aggregate time-varying component capturing macroeconomic effects common to all firms (*SDtd*, based on $N\sum_{t=1}^{T_i}(y_{.t}-y_{..})^2$); the residual time-varying component (*SDre*, based on $\sum_{i=1}^{N}\sum_{t=1}^{T_i}(y_{it}-y_{i.}-y_{.t}+y_{..})^2$). *SDbe* exploits the cross-section dimension of panel data and measures the permanent differences among individuals. The sum of the last two components (*SDtd* and *SDre*) is the within variability that exploits the time dimension of panel data and measures the transitory departures from individual averages due to both business cycle and the evolution of individual-specific characteristics. This decomposition is obtained from a STATA procedure (available upon request) written by the author and inspired by Sevestre (2002).

Tab. 3 – Persistence in Italian and US variables by pooling together micro data *[(a)]*

		Italy *[(b)]*		**USA**
Variable	Description	With zero R&D	W/out zero R&D	Bloom (2007)
$\Delta Y_{it} / Y_{it-1}$	Sales' growth	-0.046	-0.050	0.082
$\Delta E_{it} / E_{it-1}$	Employment growth	0.088	0.076	0.095
I_{it}^{m} / Y_{it}	Machinery on sales	0.132	0.241	0.274
I_{it}^{r} / Y_{it}	R&D on sales	0.563	0.698	0.690

([a]) Estimates of the second-order autocorrelation coefficients.
([b]) With zero R&D = full sample; w/out zero R&D = full sample where observations with R&D=0 are dropped

Tab. 4 - Estimates of alternative models for R&D investment with alternative estimators

Specification: [a]	Expectations model	Plans-scaled model	Accounting model	Expectations model	
Estimator: [b]	GMM-dif	GMM-dif	GMM-sys	OLS-pooled	OLS-dif
Initial cond. (IC), β_1	0.868 ***	0.869 ***	0.663 ***	0.931 ***	0.628 ***
	0.006	*0.005*	*0.104*	*0.013*	*0.023*
Sales' growth (G), β_2	0.010 ***	0.028 ***	-0.024 **	0.004	0.004
	0.001	*0.001*	*0.011*	*0.005*	*0.005*
Uncertainty (U), β_3	-0.015 ***	-0.020 ***	0.024	0.031 ***	-0.005
	0.002	*0.002*	*0.034*	*0.006*	*0.007*
Delay $IC{\times}U$, β_4	0.176 ***	0.527 ***	0.473	-0.929 ***	0.451 **
	0.030	*0.034*	*0.794*	*0.091*	*0.152*
Caution $G{\times}U$, β_5	-0.119 ***	-0.119 ***	0.093 *	-0.067 *	-0.068 **
	0.006	*0.006*	*0.058*	*0.027*	*0.024*
Cash flow (CF), γ_1	0.071 ***	0.080 ***	0.033	0.007	0.031 ***
	0.002	*0.002*	*0.054*	*0.004*	*0.008*
Debt (D), γ_2	0.004 ***	0.002 **	0.000	0.002	0.005
	0.001	*0.001*	*0.015*	*0.002*	*0.003*
N×T	3980	3980	2619	3980	2129
N	1712	1712	1071	1712	876
Average T	2.32	2.32	2.45	2.32	2.43
Resid. Autocorr. *(p-vals)*					
- 1st order	0.004	0.017	0.001		
- 2nd order	0.491	0.453	0.183		
- 3rd order	0.536	0.559	0.425		
Hansen J test *(p-val)*	0.190	0.371	0.251		
Diff-overid. *(p-val)* [c]	0.000	0.000	0.216		
R^2	0.71	0.71	0.52	0.73	0.44

[a] The summary of the three specifications is in Table 1.

[b] GMM-dif = Arellano and Bond (1991); GMM-sys = Blundell and Bond (1998); OLS-pooled = omits individual effects; OLS-dif = data in difference. Below the estimates, robust standard errors are reported in Italic. ***, **, and * respectively denote 1, 5 and 10% significant.

[c] Difference in Hansen statistic that tests the additional moment conditions used in the level equations. When the test rejects, in that column the GMM-dif approach is used, while the non rejection entails the use of GMM-sys; see the row "Estimator".

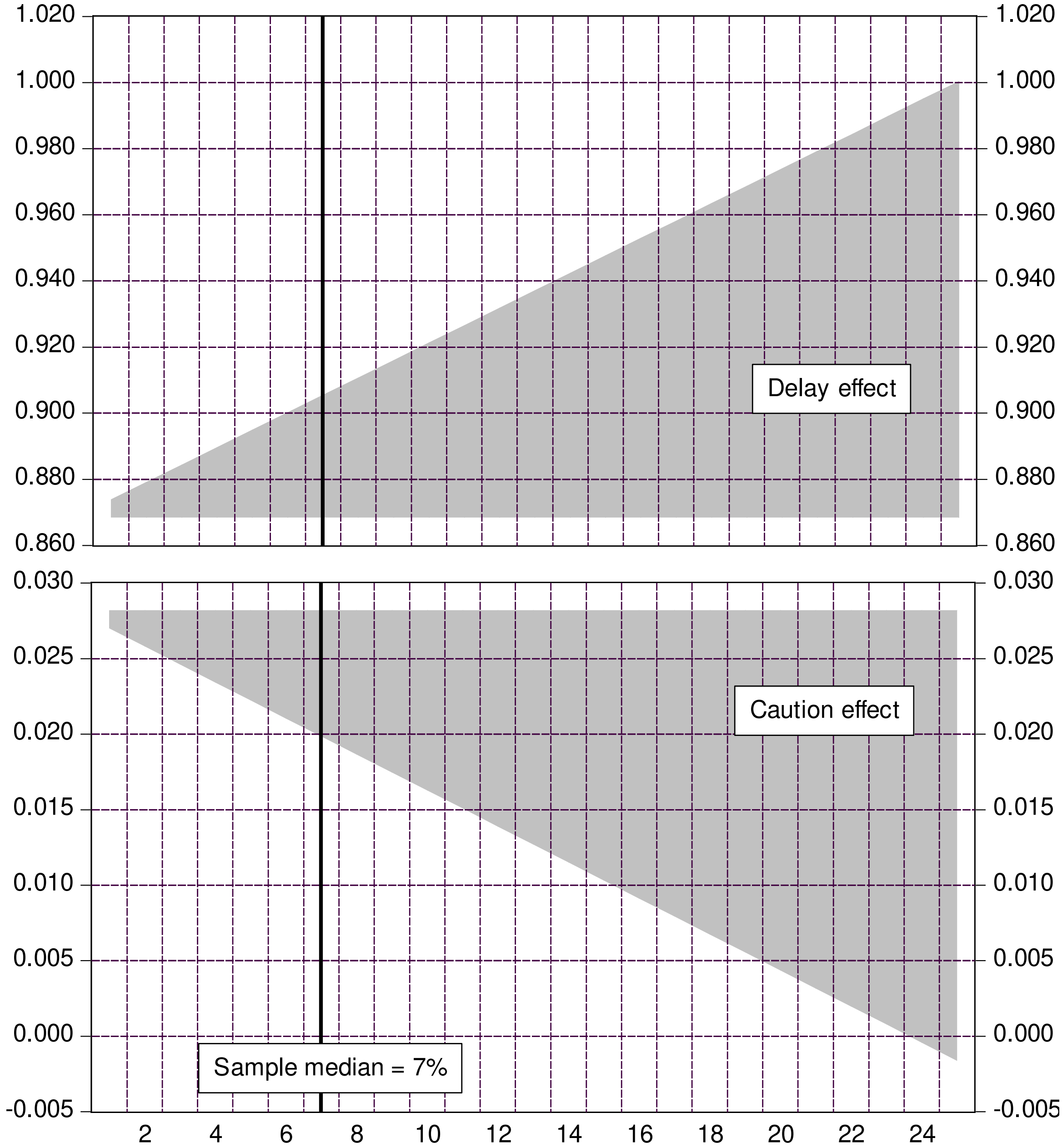
Tab. 5 - GMM-dif estimates of the plans-scaled model for alternative investments [(a)]

Investment type:	*R&D*		*Aggregate*		*Machinery*		*Buildings*		*non-R&D intangibles*	
Estimates [(b)]	$j = r$		$j = a$		$j = m$		$j = f$		$j = nr$	
Initial cond. (IC), β_1	0.869	***	0.363	***	0.265	***	0.396	***	-0.008	
	0.005		*0.030*		*0.020*		*0.013*		*0.018*	
Sales' growth (G), β_2	0.028	***	0.050	***	0.058	***	0.018	***	0.007	***
	0.001		*0.008*		*0.008*		*0.004*		*0.001*	
Uncertainty (U), β_3	-0.020	***	0.054	***	-0.013		0.031	***	-0.001	
	0.002		*0.014*		*0.013*		*0.006*		*0.001*	
Delay $IC{\times}U$, β_4	0.527	***	-0.568	***	-0.332	**	-0.734	***	1.604	***
	0.034		*0.123*		*0.164*		*0.090*		*0.132*	
Caution $G{\times}U$, β_5	-0.119	***	-0.040		-0.094	***	0.010		-0.019	***
	0.006		*0.025*		*0.022*		*0.011*		*0.003*	
Cash flow (CF), γ_1	0.080	***	0.102	***	0.042	**	-0.013		-0.006	***
	0.002		*0.021*		*0.019*		*0.008*		*0.001*	
Debt (D), γ_2	0.002	**	0.002		0.001		0.002		0.001	**
	0.001		*0.005*		*0.004*		*0.002*		*0.001*	
N×T	3980		8884		12208		5429		8658	
N firms	1712		3376		4340		2337		3343	
Average T	2.3		2.6		2.8		2.3		2.6	
Resid. autocorr. (*p-vals*)										
- 1st order	0.017		0.000		0.003		0.002		0.817	
- 2nd order	0.453		0.492		0.668		0.791		0.828	
- 3rd order	0.559		0.185		0.226		0.573		0.400	
Hansen J test (*p-vals*)	0.371		0.487		0.473		0.515		0.212	
R^2	0.71		0.45		0.46		0.32		0.27	

[(a)] For $j = m$ (machinery, equipment, vehicles), f (buildings), nr (non-R&D intangibles), r (R&D), a is the sum of the previous four categories.

[(b)] The estimates of individual and time dummy parameters are omitted. Below the estimates, robust standard errors are reported in Italic. *** and ** respectively denote 1 and 5% significant.

Fig.1 – Delay and caution effects of growing uncertainty in the plans-scaled model [a]



[a] Based on the estimates of the plans-scaled model in the second column of Table 4.
The upper vertical axis measures a dynamic delay effect, defined as $\beta_1 + \beta_4\, u({}_t g_{it+1})$, which grows with uncertainty (measured along the horizontal axis) because the estimate of β_4 in the plans-scaled model is positive.
The lower vertical axis measures a caution effect, defined as $\beta_2 + \beta_5\, u({}_t g_{it+1})$, which decreases with uncertainty because the estimate of β_5 in the plans-scaled model is negative.
On the horizontal axis the levels of uncertainty (measured as the range between the max and the min expected sales' growth) are reported for a range from the 5th to the 95th centile of its sample distribution. The median uncertainty is equal to 7%, corresponding to the vertical line.
Both the upper area of the delay effect and the lower area of the caution effect in grey get larger with uncertainty.

Appendix A1 – The sources of company data

The SIM survey is conducted annually since 1984 by the Bank of Italy. It is based on a representative[21] sample of about 1,000 Italian industrial firms with 50 or more employees in each cross-section; since 2001 manufacturing companies with 20 to 49 employees were added; and, since 2002, non-financial private service firms with 20 or more employees were also added to the survey, leading to more than 4,000 companies in each cross-section.

Together with characteristics of the firms (location, ownership structure, industrial sector, year of foundation and so on), detailed information on investment and employment decisions in the two years preceding the interview and plans for the following year is also collected. In particular, disaggregated information on tangible investments (in machinery and in buildings) is available since 1992; investment in non-R&D intangibles (see their definition below) is included since 1999; expenses in R&D are available since 2003; investment plans started to be surveyed since 1996.

The SIM collects the firms' expected demand over the next year (and also over the next three years in the 2005 Survey), and a measure of its uncertainty (very detailed in the 1993 and 2005 Surveys).

The 1984-2012 SIM sample (after deleting few outliers) is composed by 9,961 companies (3,690 with employees from 20 to 49 and 6,271 with 50 or more employees) for a total of 61,169 observations.

Table A1 describes the distribution of SIM sample according to the sector of economic activity, the size and the age of the companies. Size is based on the number of employees (the exact definition is in Section A2.4), and age comes from the year of foundation. We define 28 sectors of economic activity according to an elaboration of the NACE rev. 1.1 2-digit classification. In particular, Agriculture/hunting and forestry, Fishing, Construction, Financial intermediation, Public administration and defence and compulsory social security Education (sections A, B, F, J, L, M) were excluded from the analysis (sections N, O, P, Q are not present in the SIM database); the manufacturing industries (Section D) were classified according to their global technological intensity at the 4-digits level;[22] Electricity/Mining includes Sections C and E; section K was disaggregated into Adv/R&D/Com (with computer and related activities also adding telecommunications from section I) and Other bus.serv (renting and consultancy).

Coherently with the characteristics of the Italian economic system, the prevailing industries are Textile, Fabricated metal products, Non-electrical machinery and equipment, Food, Wholesales. The majority of enterprises is small and medium size (SMEs) [23], usually unlisted and privately held (see also Bianco et al. [2013] Table 1).

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[21] The SIM sample is stratified by firm size (number of employees), branch of activity and regional location. Thanks to the country-wide coverage of Bank of Italy's branches and their continuous interaction with the local productive and financial system, the SIM achieves high response rates, ranging from 70% to 80%. Each time a survey was run, no respondents are replaced by other firm in the same branch and size class. Estimates of the distribution of investments by branch of activity deducted from SIM are similar to those obtained from official sources, such as the NA and ISTAT's Survey of Enterprises (see Bank of Italy, 2005). Updated and very detailed descriptions on SIM sample design, response behaviour, data quality checks in each year are available at the Bank of Italy web site: http://www.bancaditalia.it/statistiche/indcamp/indimpser/boll_stat.

[22] High technology industries (HT) are Aerospace, Computer, Electronics, Pharmaceutical; Medium-High technology industries (MHT) are Scientific Instruments, Motor vehicles, Electric machinery, Chemicals, Other transport equipment, Non-electric machinery; Medium-Low technology industries (MLT) are Rubber and plastic products, Shipbuilding, Manufacturing n.e.c., Non-ferrous metal, Non-metallic mineral products, Basic metals and Fabricated metal products, Coke and refined petroleum products; Low technology industries (LT) are Pulp and paper, Textile-clothing, Food, beverages and tobacco, Wood.

[23] According to the European Commission (2003-05-06) "Recommendation 2003/361/EC: SME Definition" the category of small and medium-sized enterprises (SMEs) is made up of enterprises which employ fewer than 250

Table A1 (a) and (b) here

The classification by industry reveals the predominance of manufacturing over services (80% versus 17%), and a minor role for the Mining/Electricity sector (3%); many firms were founded in the 1970s and 1980s; old firms prevail in the Manufacturing, while young companies in Services and Mining/Electricity.

Focusing on investment in both physical and intangible capitals restricts the available time span to the 2003-2012 period. Information on both realized and planned disaggregated investments is available for 4,876 companies (15,823 observations). Such a reduction (74%) of the initial observations does not alter the sample composition by sector of economic activity, size and age.

SIM data-set has a good overlapping with the CADS database which is available since 1982 for about 129,660 companies (more than 1,115,000 observations). The merge of SIM with CADS does not alter the representativeness of the sample; this result is quite important, as CADS furnishes supplementary information to SIM (to initialize the Perpetual Inventory Method, PIM, and to compute financial variables).

CADS is provided by *Centrale dei Bilanci* - a company set up jointly by the Bank of Italy, the ABI (Italian Banking Association) and other leading Italian banks - and collects highly disaggregated balance-sheet, profit-and-loss data and flow of funds, as well as detailed information on characteristics of Italian companies operating in a wide range of industrial and service sectors. CADS is highly representative of the population of Italian firms, covering over 50% of the value added by those companies included in the Italian Central Statistical Office's Census. Further details of this dataset can be found in Bontempi (2002).

Appendix A2 –The variables' definition

A2.1 – Effective and planned investments and the capital stock

Realized and planned investments at current prices are available in SIM, disaggregated in four j types of goods: (1) $j = f$ non-residential buildings; (2) $j = m$ plants, machinery and equipment; (3) $j = nr$ non-R&D intangibles; (4) $j = r$ R&D. In particular, they are gross fixed investment (the depreciation is included) referring to the acquisition[24] of fixed capital to the firms' asset in the reference period; fixed capital derives from a production process and can be used repeatedly in the production of goods and services for more than one year.

Item $j = f$ includes the buildings under construction and new-built, and the expenditure for the renovation of already existed plants; grounds and the used residential buildings are excluded from the figure. The investment in plant under construction is equivalent to the sum of the received invoices during the reference period from the contractors and/or the value of the plant construction built directly by the firm.

Item $j = m$ includes plants, tools and machinery, hardware (available separately in 2005 and 2010 only), means of transport and used tangible assets (expenditure for physical second-hand assets which refers to the purchase of goods that was before used by other companies in their production process; neither the purchase of second-hand land and residential buildings, nor the goods involved in a company's merger or acquisition are included). For the under construction item,

persons and which have an annual turnover not exceeding 50 million euro, and/or an annual balance sheet total not exceeding 43 million euro.

[24] The acquisition includes: a) preventive and proactive maintenance and the share of the corrective maintenance, invoiced by the suppliers, that could be capitalized by law; b) production and repair of own capital goods made by the firm and capitalized.

only the corresponding value of the sum of the received invoices during the reference period from the contractors and/or the value of the capital good directly set-up by the firm is included.

Item $j = nr$ - non-R&D intangibles - consists of software, mineral exploitation, copyright on entertainment and works of literature and art. Software also includes the software realized in house (in this case the development should be valued at an estimated price or, if it is not possible, at its production cost) and the expenditure for database that was used in the production for more than one year. Mineral exploitation includes also the test drilling, survey flights or other survey, transportation cost. In $j = nr$ copyright protected entertainment, literary and artistic originals (like movie, audio record, manuscript, model) are included. Note that patents, marketing and advertising costs are excluded from investment in $j = nr$.

Item $j = r$ is expenditure on R&D, market research, design and test products; both the purchased services from an external company and the one developed in house are included; any costs for software development and expenditure on education and training are excluded.

For the i^{th} company ($i = 1, 2, \ldots, N$) at year t ($t = 1, 2, \ldots, T$), we indicate with INV_{it}^{j} and ${}_{t}INV_{it+1}^{j}$ the level of effective investment realized in t, and of the investment planned in t for $t+1$, respectively; the superscript j (= f, m, nr, r, a) indicates the type of good, with a denoting the aggregation over the four typologies. Figures at constant (2000) prices are obtained as $I_{it}^{j} = INV_{it}^{j} / PI_{nt}^{j}$, where the NA sectoral investment prices PI_{nt}^{j} for all the companies belonging to n^{th} industry are used as deflator for realized investments. In the case of plans we use ${}_{t}I_{it+1}^{j} = {}_{t}INV_{it+1}^{j} / {}_{t}PI_{it+1}^{j}$, with ${}_{t}PI_{it+1}^{j} = (1 + {}_{t}\pi_{it+1}^{j})PI_{nt}^{j}$, where ${}_{t}\pi_{it+1}^{j}$ is the expected inflation of the j-type investment price (estimated from the SIM source).[25]

A problem in comparing Italy and major OECD economies is related to the different accounting systems as stated by the GAAP (Generally Accepted Accounting Principles): in Anglo-American countries R&D is expensed as it is incurred, rather than capitalized and depreciated, which means that the lifetime of the investment for accounting purpose is much shorter than the economic life of the asset created.[26] Notwithstanding criteria employed in recognizing intangible assets are similar to those of the IAS/IFRS,[27] Italian GAAP (as well as other European country with a Continental accounting basis) present a specific list of intangibles that should be capitalized (classified as fixed assets) in the balance sheet: in our context, item $j = nr$ is mainly composed by deferred charges (like start-up and expansion expenses) and items (like patents and intellectual property rights, concessions, licenses, trademarks and similar rights) that are capitalized as assets and thus treated as valuable investments. As far as item $j = r$ is concerned, it includes: applied research and development costs, and advertising costs functional and essential to the start-up phase which are capitalized; basic research expenses and regular license-fees paid for patents which are instead recognized as costs when incurred.[28]

[25] The expected inflation is available for total tangible investment and for software expenses. For buildings and machinery (software and R&D) ${}_{t}\pi_{it+1}^{j}$ is estimated by ${}_{t}\pi_{it+1}^{j} = {}_{t}\pi_{it+1} - (\pi_{nt+1} - \pi_{nt+1}^{j})$, where $\pi_{nt+1} = (PI_{nt+1} - PI_{nt}) / PI_{nt}$ is the total investment price inflation on goods f and m (nr and r), and $\pi_{nt+1}^{j} = (PI_{nt+1}^{j} - PI_{nt}^{j}) / PI_{nt}^{j}$ is the j-type investment price inflation rate for $j = f, m, nr, r$.

[26] For an international comparison of accounting principles on intangibles, see Stolowy and Jany-Cazavan (2001).

[27] An intangible asset should be recognized at cost if and only if it is identifiable, it is probable that specifically attributable economic benefits will flow from the assets, and its cost can be measured reliably.

[28] On average expensed R&D and patent-fees represent a mere 7% of good r. Operative and recurrent advertising is excluded from good r .

A2.2 – Expectations and uncertainty about future demand

The level of sales at constant prices is $Y_{it} = SAL_{it} / PY_{it}$, where SAL_{it} is the value at current prices of the i^{th} company's sales in *t* taken from SIM database, and PY_{it} is the individual sales' deflator taken from NA.[29]

Since the 1996 survey, firms are first asked for their projected percentage change in nominal sales from *t* to *t+1*, then they are asked for the annual growth in their sales' price, and finally the percentage changes of sales in real terms ${}_t g_{it+1}$ are given by the difference of nominal growth minus the expected inflation.

Given the base prediction ${}_t g_{it+1}$, firms indicate a range around this figure, i.e. provide a minimum and maximum expected real turnover. We can obtain our uncertainty measure about the future demand growth $u({}_t g_{it+1})$ defined as the min-max range of sales' expected growth rate reported by SIM respondents.

These data are available for an unbalanced panel of 33,919 observations for 7,550 individuals (on average more than 1,990 firms per year in the 1996-2012 period with average T equal to 4). Although less informed than the knowledge of the whole subjective probability distribution of respondents about future demand,[30] the main advantage of $u({}_t g_{it+1})$ measure of uncertainty is that of being available for each year of the whole time span 1996-2012.

From the individual expected growth rates ${}_t g_{it+1}$ we can also proxy the disagreement of expectations, labelled as $se_{st}({}_t g_{it+1})$, with the standard deviation of the expected growth rates in sector-year clusters. The years are 17 (from 1996 to 2012), and the sectors are 28 (classified according to the NACE rev. 1.1 classification, described in section A1).

A2.3 – Financial variables

Cash flow, net of dividends paid. Individual data at current prices are derived from the CADS database: CD_{it} = cash flow (item 9.14) minus dividends (item 7.6); this figure has been compared and updated by the information in SIM (fi12, fi14, fi16). In order to obtain data at constant prices, CD_{it} has been deflated using PY_{st} (the by-industry production deflator from NA, see e.g. Bond and Meghir [1994]): $CF_{it} = CD_{it} / PY_{st}$.

Financial debt. It is defined, from CADS, as the sum of short- and long-term bank debt (items: 4.26-678-679-683 + 4.2-648-649-684) plus the sum of short- and long term financial debt versus other financial institutions and group (items: 4.27-477-483+274-601-603-604-606-676-677 + 4.22-600-602-605-646-647). Missing information has been filled by SIM (fi11, fi13, fi15, fi21, fi26, fi36). As in the cash flow case, nominal book values have been deflated by using PY_{st} (the by-industry production deflator from NA); its label is D_{it} . The use of book – instead of market - values of debt is appropriate when, as in our case, short-term overwhelms long-term debt and companies are unlisted (see also Lang et al. [1996]).

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[29] Actually, individual sales' deflators are obtained by applying the SIM growth rate for year *t* to the previous year NA deflator level of the sector to which the firm belongs. We use NA sector deflator levels when SIM growth rates are not available.

[30] This is available in SIM dataset only for two years (1993 and 2005). In the 2005 survey the question about the min max range was substituted for by a more complex one on the firms' subjective probability distribution. For this, the min-max range data for 2005 are obtained as in Bianco et al. (2013) See Guiso and Parigi (1999) for the use of uncertainty based on the subjective probability distribution of respondents in 1993.

Constant-prices financial variables above have been scaled by real sales.

Credit rationing indicator (*RAT1*) It is equal to one if the firm is credit-constrained according to the "yes" answers to questions on access to credit provided by SIM: (i) at the terms and conditions (cost and collateral) currently applied, the firm would like to borrow more from banks or other lenders; (ii) whether the firm would be willing, at present, to pay a higher rate of interest or even to accept tighter terms and conditions in order to borrow more; (iii) the firm actually applied for new loans from banks or other financial intermediaries, but she was granted only part of the amount requested, or she was given no loan because the financial intermediaries contacted were not willing to grant the loan, or no loan was obtained for other reasons (e.g. cost or collateral considered to be excessive); (iv) the creditors asked the firm for early repayment of loans granted in the past; (v) the firm's overall borrowing conditions became worse in the general conditions or in specific aspects like interest rates, other costs (banking fees, etc.), amount of collateral required, access to new financing, time necessary to obtain new funds, complexity of information needed to obtain new funds, requests of reimbursing previously granted loans beforehand; (vi) if the firm indicated that her overall borrowing conditions "became worse" between the first and second half of *t*, she will take measures to limit the effects of this, and the high-preponderant measures are the use of liquid assets (e.g. reduction of bank balances, sale of government securities), the reduction of the debt level and the reduction of planned investment.

A2.4 – Other non-financial variables

Employees: Average number of workers (blue-collars, apprentices, white-collars, managers) in the firms. The figures include the owner or the partners if they work in the firm. Also, the figures are inclusive of the workers with a fixed-term contract and the subsidized short-time workers (CIG); for the part time and seasonal workers, the corresponding number of workers is multiplied by the fraction of the year in which they work; the subsidized short-time workers are considered wholly in the figure.

Group: equal to one if the firm belongs to a group.

FA: Equal to one if the firm identified herself as a "family" firm, defined as a "firm that is directly or indirectly controlled and managed by an individual or a group of individuals linked by family relationships". The respondents are asked to identify "control" with the actual possibility to take strategic decisions in the firm: this might be the result of the ownership of a majority of shares or of the presence of control enhancing mechanisms (such as pyramids, dual class shares, voting agreements) that – even without a majority of shares – allow some agents to take the most important decisions for the firm. We checked this classification by exploiting two specific questions: a) "whether the firm did not change control since its foundation" and in case it did, b) whether before the change it was a family or nonfamily firm" (hence we include firms that are controlled by a family which is not necessarily the founding family). Further details on this classification and family firms' characteristics are in Bianco et al. (2013).

Age: Age of the firm, defined as the difference between the survey year and the year of foundation of the firm.

RED: Equal to one if the firm engaged in R&D in 2008-2010 and 2009-2011 periods.

PAT: Equal to one if, from 2008 to 2010, the firm filed for a patent, registered an industrial design or trademark.

PROC: Equal to one if, from 2008 to 2011, the firm engaged in production process innovation.

PROD: Equal to one if, from 2008 to 2011, the firm engaged in product innovation.

ORG: Equal to one if, from 2008 to 2011, the firm engaged in organizational and operational innovation.

red_Internal, red_Group, red_ItUniv, red_ForUniv, red_ExtFirm: Equal to the percentages according to which the R&D expenditure in 2008-2010 was apportioned by in-house or outsourced to another member of the firm's group or outsourced to Italian universities and research centres or outsourced to foreign universities and research centres or outsourced to non-group firms or consultants, respectively (used in Table A2 (b)).

red_Autofin, red_Debt, red_EqVC, red_Pubfin, red_other: Respectively equal to the percentages according to which the R&D spending in 2008-2010 and 2009-2011 was financed by: self-financing or intra-group funds; banks and other financial intermediaries; equity or venture capital; public funding; other funds (used in Table A2 (b)).

Highperblue: Equal to one for firms having a percentage of the staff that had university or higher training (all university degrees: regular, three-year, advanced, master's, doctorates, etc.) greater than the median of the sample.

INT: Equal to one for firms producing goods or services abroad, or even just contemplating locating part of their production abroad (through ownership/control of foreign companies, direct ownership of local units, trade agreements, technical and production agreements, R&D).

INTRED: Equal to one for firms engaged in major collaboration agreements with foreign companies for joint designing and planning, research and the like activities.

Appendix A3 – Additional features about R&D and firms investing in R&D

Figure A1 compares the change in investment composition between the two sub-periods 2004-2007 and 2009-2012. The pattern of R&D is in line with OECD (2013, p. 39) and shows that investment in R&D by both the business sector and the services generally grows more than investment in physical capital, despite negative changes in financing availability and aggregate demand due to the Great Recession. This similarity is reached even if the measure of our expenditures in knowledge-based capital is not primarily or only wages (which tend to be stickier than other forms of business expenditures).

Figure A1 here

The sectors of economic activities are ordered, from top to bottom, according to increasing labour productivity; this placement does not mirror the high-technology intensity of manufacturing and services.[31] The figure shows a widespread increase in R&D percentage, especially in computer, non-electric machinery, electronics, motor vehicles and pharmaceutical, while aerospace increased the percentage of machinery. Pharmaceutical enlarged the R&D investment and gained a higher position according to the labour productivity; shipbuilding reduced R&D and increased labour productivity.

In order to better understand the nature of the investment in intangibles, we exploited some qualitative information available in SIM database and defined in Appendix A2. Results are reported in Table A2.

Table A2 here

[31] The same picture with industries ordered according to the percentage of sales over advertising shows shipbuilding, motor vehicles, rubber and plastic, petroleum, aerospace at the higher positions. Pharmaceutical, ADV/R&D/Com, scientific instruments display low percentages like the low-technology industries (food, paper, textile, wood).

Table A2(a) compares the shares of firms declaring to engage in R&D (*RED*) in the two periods 2008-2010 (2010 survey) and 2009-2011 (2011 survey). The percentage is significantly lower in the second period, as evidenced by the "Diff" and "P-val" last two columns. In the following rows, the "Diff" and "P-val" columns compare the percentage of firms that filed for a patent (*PAT*), engaged a production process (*PROD*) or a product (*PROC*) or an organizational innovation (*ORG*) conditionally on the declaration of doing or not doing R&D. We also show the frequency of: (1) firms engaging or not R&D according to having a large percentage of high-level trained workers (*Highperblue*); (2) being credit rationed (*RAT1*); (3) the ownership composition (being a family firm, *FA*, or being part of a group, *group*); (4) being present abroad (*INT* and *INTRED*). Firms investing in R&D produce more frequently products' innovation, followed by process and organizational innovations. This rank does not change in 2011, while the corresponding frequencies are reduced in accordance with the lower percentage of firms doing R&D. Firms spending in R&D have also a large percentage of university graduates among entrepreneurs, senior and junior managers, and production workers and apprentices; these companies belong to a group and have decided to internationalize their activity.

Table A2(b) compares the operational and financial sources of R&D activity in two years, 2010 and 2011, and depending on the ownership structure (family or group) and whether a firm is credit rationed. Figures show that the largest part of R&D is in-house produced and internally financed. Debt is the second source of financing, followed by public funding that however is comparatively lower.[32] Firms using more public financial support are those credit-constrained.[33] Since 2008, the enduring economic crisis reduced the yet infrequent use of equity and venture capital to finance innovation, independently from being or not credit-constrained. Collaboration with Italian Universities or Research Centres is higher for not credit-rationed companies.[34]

Appendix A4 – Investment patterns over time: volatility, persistence and co-movements

In this appendix, the evidence about micro data (in Section 4) is validated through the comparison with the macro evidence for Italy, to assess whether both data sources embody similar stylized facts.[35] We exploit classical business-cycle time-series tools (see e.g. Schlitzer [1995]) based on three cyclical indicators estimated over the backwards-enlarged span 1984-2012. The extended time period allows for a better assessment of the data features. The use of NA data facilitates the availability of longer time series at the macro level. Regarding micro data, the problem of short time (2003-2012 for R&D) spanned by SIM has been tackled by backward extending SIM data with CADS, as the latter provides disaggregated information for different types of investment since 1982 (see Appendix A1).

As far as the cyclical volatility is concerned, macro aggregated investment is almost four times more volatile than GDP. Among the components, real R&D expenditure is the least volatile, with estimates significantly lower than those for machinery, non-R&D intangibles and, to a lesser extent, buildings. The averages of individual micro cycle indicators confirm the macro outcome for R&D and Non-R&D intangibles, while for tangibles the variability is slightly lower than the macro one. Overall, macro data suggest that investments in machinery and Non-R&D intangibles are noisier than those in buildings and R&D, while micro data highlight the larger volatility of R&D

[32] In the 2010 and 2011 surveys there was a question on whether the R&D spending would have been of the same or more or less amount without receiving public funding. The main part of the companies declared the same or a higher amount; from 2010 to 2011 the percentage of firms declaring a lower amount increased by 6 percentage points.
[33] The firms which more frequently used public finance did not apply for new loans from banks or other financial intermediaries because they were convinced that their application would be rejected.
[34] Some further descriptive analysis (not reported but available upon request) shows that a high percentage of firms collaborating with Italian universities was asked by the creditors for early repayment of loans granted in the past.
[35] Details about the techniques we used and the full set of results are available upon request.

and Non-R&D intangibles. The latter result is greatly amplified if we pool together individual micro data to estimate cyclical indicators rather than averaging individual indicators: the volatility of Non-R&D intangibles is almost seventy times that of real sales growth, and the volatility of R&D is even bigger. The variances estimated by pooling micro data show a volatility of intangibles which is vastly larger than that of both intangible at the macro level and tangibles at the micro level.[36]

As far as the persistence over the cycle is concerned, macro R&D spending over GDP is the most persistent: we can say - in cointegration jargon - that R&D and GDP levels do not share a common trend. Therefore, the share of R&D on GDP does not revert very often to its historical mean over time, and this fact induces large estimates of the autocorrelation coefficients. Micro data confirm the significant persistence found at macro level, although at lower levels (about less than half of macro estimates). The large number of observations available in the longitudinal dimension, together with the short temporal span, explains the lower levels of autocorrelation (persistence), and their high significance. Across categories, the aggregate investment is more persistent than its components (both tangible and intangible), and this difference tends to increase with the number of zeroes in the disaggregate series: investment ratios of buildings and R&D are less persistent than those of machinery and plants.[37]

As far as co-movements of investments with cycle indicators are concerned, macro outcomes suggest that tangible investments are pro-cyclical and coincident with GDP. Micro data confirm this cyclical features of tangibles, while present a less evident picture for intangibles which partly contrasts with the clearer a-cyclicality of macro R&D and Non-R&D intangibles. Overall, we can label intangibles as a-cyclical, although this view is more subject to lacking clear-cut evidence than that for tangibles.

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[36] It is worth noting that such micro variability of intangibles is not merely due to the presence of many cases of individual zero expenditure in R&D, as the R&D variability would have further *increased* (and not decreased) if we computed it by excluding all these zeroes. This outcome suggests that the presence of spikes explains the large R&D micro variability, and that these spikes do not only occur when the expenditure was zero in the previous year. Conversely, the exclusion of zero R&D observations drops invariant observations that, if left in the sample, would deflate the estimate of variance.

[37] Oppositely to what happens for variability, the exclusion from the sample of the observations with zero R&D increases persistence. The presence of zeroes negatively contributes to the estimate of the micro R&D persistence, as the negative contribution to covariance estimates (due to positive spikes occurring when the expenditure in *t-1* was zero i.e. below the average) is larger than the negative contribution to variance estimates (due to a number of zero expenditures).

Tab. A1(a) - Sample percent composition: by industry and size

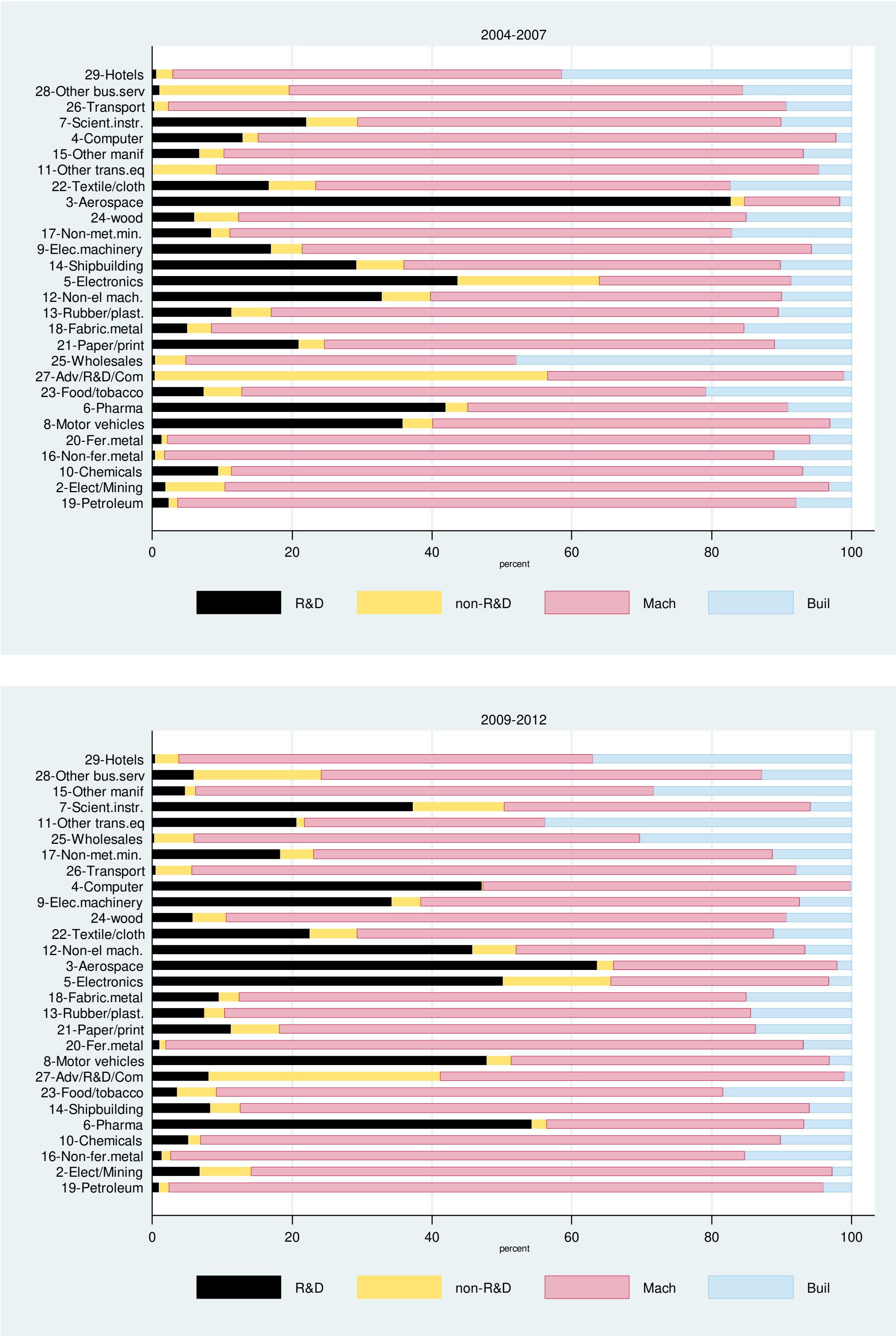
	Size (number of employees)					
Industry	1-49	50-99	100-199	200-499	≥ 500	Total
2-Elect/Mining	1.20	0.66	0.43	0.33	0.32	2.94
3-aerospace	0.04	0.04	0.05	0.08	0.21	0.43
4-computer	0.04	0.06	0.04	0.15	0.21	0.50
5-electronics	0.14	0.12	0.10	0.18	0.21	0.75
6-pharma	0.08	0.17	0.15	0.39	0.85	1.64
7-scient.instr.	0.33	0.26	0.21	0.28	0.32	1.40
8-motor vehicles	0.37	0.38	0.45	0.65	1.23	3.07
9-elec.machinery	0.73	0.73	0.56	0.71	0.89	3.62
10-chemicals	0.80	0.55	0.69	0.81	0.81	3.66
11-other trans.eq	0.03	0.00	0.00	0.02	0.00	0.05
12-non-el mach.	2.12	1.97	2.33	1.83	2.14	10.39
13-rubber/plast.	1.25	0.87	0.70	0.67	0.47	3.96
14-shipbuilding	0.21	0.09	0.19	0.19	0.12	0.80
15-other manif	0.09	0.06	0.05	0.09	0.02	0.32
16-non-fer.metal	0.12	0.08	0.16	0.18	0.17	0.70
17-non-met.min.	2.13	1.25	1.29	1.02	0.88	6.57
18-fabric.metal	3.27	2.69	2.10	1.85	0.56	10.47
19-petroleum	0.24	0.05	0.09	0.12	0.10	0.60
20-fer.metal	0.19	0.22	0.21	0.28	0.34	1.24
21-paper/print	0.94	0.97	0.66	0.78	0.74	4.08
22-textile/cloth	2.61	2.97	2.29	2.41	1.33	11.61
23-food/tobacco	3.43	2.15	2.05	1.29	1.04	9.96
24-wood	1.45	1.03	0.67	0.87	0.21	4.23
25-Wholesales	3.24	1.40	1.07	0.75	0.87	7.33
26-Transport	1.16	0.70	0.58	0.94	0.78	4.15
27-Adv/R&D/bus.serv	0.34	0.28	0.24	0.21	0.20	1.26
28-Other bus.serv	0.57	0.57	0.53	0.57	0.50	2.74
29-Hotels	0.64	0.28	0.24	0.14	0.21	1.53
Total	27.77	20.60	18.14	17.79	15.70	100.00

Note: Adv/R&D/bus.serv includes communication and computer. Other bus.serv are professional services, like accounting, auditing, legal, tax consultancy as well as architectural and engineering activities and related technical consultancy.

Tab. A1(b) - Sample percent composition: by macro-industry and age

	Age (year of foundation)						
Industry	1-'40 and	2-'50	3-'60	4-'70	5-'80	6-'90	Total
2-Mining/electric	0.39	0.22	0.32	0.42	0.45	1.14	2.94
3-Manufacturing	15.38	7.67	13.19	14.99	15.85	12.98	80.05
5-Wholesale/Hotels/Transport	1.24	0.65	1.28	2.59	3.72	3.67	13.14
6-Other services	0.18	0.13	0.15	0.92	1.27	1.23	3.87
Total	17.19	8.66	14.94	18.91	21.29	19.01	100.00

Fig. A1 – The composition of investment in physical and intangible capital by industry



Note: Moving from top to bottom industries are ordered according to the highest percentage of sales over employees.

Tab. A2 (a) – Characteristics of R&D; 2010 and 2011 surveys

	Do firm engage R&D (*RED*)?							
	2010				2011			
	YES	NOT	Diff	P-val	YES	NOT	Diff	P-val
	0.53	0.47			0.48	0.52	-0.05	0.006
Patent registered (*PAT*)	0.52	0.13	0.39	0.000				
Process innovation (*PROC*)	0.69	0.23	0.46	0.000	0.60	0.18	0.42	0.000
Product innovation (*PROD*)	0.81	0.21	0.60	0.000	0.77	0.18	0.59	0.000
Organizational innovation (*ORG*)	0.68	0.34	0.34	0.000	0.57	0.26	0.31	0.000
High level training workers (*Highperblue*)	0.74	0.59	0.15	0.000	0.62	0.47	0.15	0.000
Credit rationing (*RAT1*)	0.53	0.49	0.04	0.190	0.69	0.65	0.04	0.048
Group	0.68	0.47	0.21	0.000	0.60	0.40	0.20	0.000
Family firm (*FA*)	0.46	0.39	0.07	0.030	0.44	0.35	0.09	0.000
Internationalization (*INT*)					0.35	0.09	0.25	0.000
Internationalization for R&D (*INTRED*)					0.22	0.06	0.16	0.000

Notes: All the variables are dummies, as described in Appendix A2.

Tab. A2 (b) – Main features of R&D; 2010 and 2011 surveys

		Ownership (2010)				Ownership (2011)			
		Family firms	Non family firms	Diff	P-val	Family firms	Non family firms	Diff	P-val
How was your R&D expenditure apportioned, by percentage?	In-house	84.57	75.65	8.93	0.012				
	Outsourced to group	2.05	7.67	-5.62	0.011				
	It. Univ./research centres	4.54	6.49	-1.95	0.341				
	For.Univ./research centres	0.24	0.20	0.03	0.822				
	Non-group/consultants	8.61	9.99	-1.39	0.563				
How was your R&D spending financed, by percentage?	Self-financed/intragroup	85.31	86.36	-1.043	0.755	82.88	86.19	-3.32	0.146
	Bank/other fin. Interm.	6.205	3.871	2.333	0.267	9.20	4.07	5.13	0.001
	Equity/VC	0.386	2.426	-2.039	0.164	0.18	0.43	-0.25	0.570
	Public funding	6.986	5.772	1.214	0.536	6.35	7.10	-0.75	0.585
	Other	1.11	1.57	-0.47	0.682	1.40	2.22	-0.82	0.398
		Group (2010)				Group (2011)			
		Yes	No	Diff	P-val	Yes	No	Diff	P-val
How was your R&D expenditure apportioned, by percentage?	In-house	79.91	87.77	-7.87	0.001				
	Outsourced to group	5.16	0.66	4.50	0.000				
	It. Univ./research centres	5.45	4.08	1.37	0.292				
	For.Univ./research centres	0.70	0.14	0.56	0.056				
	Non-group/consultants	8.79	7.35	1.45	0.400				
How was your R&D spending financed, by percentage?	Self-financed/intragroup	87.19	80.84	6.34	0.032	86.04	78.44	7.60	0.000
	Bank/other fin. Interm.	5.08	8.07	-2.99	0.139	6.56	10.13	-3.57	0.007
	Equity/VC	1.20	0.56	0.65	0.343	0.33	0.33	-0.00	0.994
	Public funding	5.48	8.08	-2.60	0.111	5.40	9.41	-4.01	0.000
	Other	1.051	2.45	-1.4	0.264	1.68	1.70	-0.02	0.979
		Credit rationing (2010)				Credit rationing (2011)			
		Yes	No	Diff	P-val	Yes	No	Diff	P-val
How was your R&D expenditure apportioned, by percentage?	In-house	84.02	80.54	3.48	0.149				
	Outsourced to group	2.567	5.07	-2.50	0.063				
	It. Univ./research centres	3.613	6.62	-3.01	0.029				
	For.Univ./research centres	0.272	0.80	-0.53	0.196				
	Non-group/consultants	9.528	6.96	2.57	0.109				
How was your R&D spending financed, by percentage?	Self-financed/intragroup	77.86	88.40	-10.54	0.001	78.52	85.93	-7.42	0.000
	Bank/other fin. Interm.	12.07	3.37	8.70	0.000	11.40	5.75	5.64	0.000
	Equity/VC	0.03	1.42	-1.39	0.016	0.39	0.29	0.10	0.718
	Public funding	9.65	4.83	4.82	0.008	8.80	5.83	2.97	0.004
	Other	0.39	1.98	-1.59	0.035	0.90	2.20	-1.30	0.026

Notes: See the definitions of *red_Internal, red_Group, red_ItUniv, red_ForUniv, red_ExtFirm* and *red_Autofin, red_Debt, red_EqVC, red_Pubfin, red_other* , and of *FA*, *Group*, *RAT1* in Appendix A2.