University R&D and Firm Productivity: Evidence from Italy

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ABSTRACT. Ed Mansfield wrote several papers on the private returns to basic research (e.g. Mansfield, 1980) and the influence of academic research on industrial innovation (e.g. Mansfield, 1991). We extend this line of research by assessing the impact of university research on total factor productivity growth of Italian manufacturing firms. The econometric analysis is based on reduced-form estimation of the R&D capital stock model, including controls for two potential sources of sample selection bias, as proposed by Crepon *et al.* (1998) and Piga and Vivarelli (2004). Our results suggest that while there are positive returns to collaborative research with other firms, collaborative research with universities does not appear to directly stimulate productivity. We interpret this result as consistent with recent evidence (e.g. Hall *et al.*, 2001, 2003) suggesting that firms engage in collaborative research with universities when appropriability conditions are weak.

Key words: university R&D, total factor productivity, sample selection bias

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1. Introduction

Ed Mansfield is probably best known for his seminal project-level research on the microeconomics of technological advance and the computation of social returns to innovation (Mansfield, 1968; Mansfield *et al.*, 1977). Professor Mansfield also wrote several papers on the private or firm-level returns to basic research (e.g. Mansfield, 1980) and also one of the first comprehensive studies of the influence of academic research on industrial innovation (Mansfield, 1991).

In this paper, we attempt to extend this line of research, by assessing the private returns to collaborative R&D with universities. Such evidence may shed light on an unexplored dimension of university technology transfer: the impact of joint research projects with universities on a firm's growth in total factor productivity (henceforth, TFP). TFP is generally regarded to be the best metric of economic efficiency.

Our empirical analysis is based on comprehensive, longitudinal surveys of Italian manufacturing firms. These files contain detailed data on output, factor inputs, and R&D investment, which we use to estimate a reduced-form version of the R&D capital stock model. The econometric analysis includes controls for two types of sample selection bias, as proposed by Crepon *et al.* (1998) and Piga and Vivarelli (2004), a variant of which was applied to an earlier version of these data in a previous paper (Medda *et al.*, 2004).

2. Econometric model

Our econometric model is a reduced-form version of the R&D capital stock model (Griliches,

1979), which asserts that there is a stock of technical capital (in addition to physical capital) in a firm's production function. If we assume disembodied, Hicks-neutral, technological progress, constant returns to scale with respect to the conventional inputs (capital, labor and materials), perfectly competitive factors markets, and we compute logarithms and differentiate the production function with respect to time, we have the following equation:

$$\text{TFPG} = \alpha + \beta_1 X_1 + u \quad (1)$$

where TFPG = growth in total factor productivity (TFP); X_1 = rate of R&D investment, typically computed as the ratio of R&D to output u = a classical disturbance term; α = the rate of disembodied external technical change.

In this type of model, TFP is computed as a Solow residual. Empirical estimates of $\beta_1$from equation (1) have been interpreted as an estimate of the marginal private rate of return to investment in R&D. Scherer (1982) noted that if the stock of R&D capital depreciates, estimates of β_1 are downwardly biased. Schankerman (1981) discusses the impact of "double-counting" in the calculation of the private returns to R&D, since R&D expenditures are often already included in measures of capital, materials, and labor (the conventional arguments of a production function). Thus, it is common in this literature to refer to β_1 as an "excess" rate of return (in excess of normal remuneration to conventional factors of production).

As noted in Link and Siegel (2003), most researchers report estimates of β_1 that are positive and statistically significant, implying that there are positive returns to R&D. There have also been numerous studies that provide evidence on *differential* returns to R&D by type (i.e. product versus process), character of use (i.e. basic research, applied research, and development), or source of funding (i.e. privately-financed R&D versus publicly-funded R&D). For instance, Mansfield (1980), Link (1981), and Griliches (1986) find that there is a productivity premium associated with basic research. Lichtenberg and Siegel (1991) report that while company-funded R&D has a positive impact of productivity, publicly-funded R&D does not.

Another important distinction in innovative activity at the firm level is between internal and external R&D. External research projects are conducted with other firms, universities, or non-profit research organizations. Such activities might enable firms to enhance their "absorptive capacity" (Cohen and Levinthal, 1989) or result in other types of beneficial research spillovers (Kamien and Zang, 2000). Hall *et al.* (2001) found that firms typically collaborate with universities when they engage in long-term, basic research projects.

We would like to estimate equation (1), using total R&D intensity, or the ratio of R&D expenditure to sales as our proxy for the rate of investment in R&D investment. More importantly, we wish to disaggregate this intensity measure into internal and external R&D intensities, in order to assess their differential returns. Further disaggregation of external R&D is made possible by the availability of data on the research relationships companies have with research centers, universities and other firms.

It is important to note that there are two potential sources of sample selection bias associated with estimation of equation (1). The first potential source of bias relates to the fact that many firms do not conduct formal R&D activities, in the sense that they report zero expenditure on R&D. Second, as noted by Piga and Vivarelli (2004), the decision to undertake external research may be related to the antecedent decision to engage in some form of R&D. Our point is that firms reporting that they have conducted external research (as some do in our survey) are not randomly selected, but rather, constitute a sub-sample of those reporting involvement in R&D.

To mitigate these problems, we propose to estimate a two-stage, treatment effects model (Barnow *et al.*, 1981). In the first stage, we estimate a bivariate probit sample selection model, in which we jointly assess the determinants of reporting positive R&D expenditure and, conditional on non-zero R&D, the determinants of external R&D activity. Formally:

$$\begin{gathered}\text{DREEXT}_i = \beta_1 x_{i1} + \epsilon_{i1}, \quad y_{i1} = 1 \\ \text{if R\&DEXT}_i > 0, \text{ 0 otherwise}\end{gathered} \quad (2)$$