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Abstract

In this paper we address the issue of if and how firm subsidies foster investment in fixed capital and R&D and by doing so they contribute to the innovation output. We therefore extend the existing literature which so far has mostly focussed on the effects of public subsidies on specific innovation inputs. By using a rich dataset on Italian firms we estimate the relationships between inputs (investments) and innovation outputs (process and product) as well as investment equations in which expected firm subsidies affect the inputs. In order to deal with endogeneity issues we propose an empirical approach which exploits the information and characteristics of our dataset. We find that expected public intervention has an effect on investment in fixed capital and innovation. The impact of firm subsidies on R&D investment is found to be somehow weaker as well as its final effect on innovation.

Keywords: Firm Subsidies, R&D and Fixed Investment, Product and Process Innovation

JEL codes: C23, H25, O32

1. Introduction

The importance of innovation for companies and—ultimately—for aggregate economic growth is now understood by policy makers.¹ In fact, innovation helps companies increase their productivity levels, enter new markets or stave off competition. It is now also commonly accepted that innovation comes in many different forms, ranging from a new product arising from R&D (product innovation) to efforts to incorporate innovative production equipment (process innovation), use new workplace practices (organizational innovation) or create new marketing concepts (marketing innovation).² At a policy level the diversity of innovation causes difficulties in understanding the process as a whole and—ultimately—in designing appropriate innovation policies and monitoring their effectiveness.

In particular, most incentive schemes implicitly aimed at stimulating innovation output are designed with the main purpose of addressing market failures, such as externalities, imperfect information or coordination problems. Those are likely to affect specific factors, including R&D and fixed investment, which enter the innovation process as inputs. Obviously, this approach has solid economic foundations and, indeed, there is general consensus among economists that market mechanisms fail to provide the socially optimal level of R&D spending, basically because private firms are not able to fully capture all the profits arising from the results of their R&D activity. Government intervention in this area is thus justified from an economic point of view by the market failure aspect of R&D: because the social returns to private R&D are often higher than the private returns, some research projects would benefit society but would be privately unprofitable. By lowering the cost to the firm, a subsidy can make these projects profitable as well. A somewhat related economic argument might also apply to fixed investment since the existence of financial constraints in some disadvantaged areas can lead to a sub-optimal capital accumulation level which in turn could be corrected by the implementation of appropriate incentive schemes.

Providing convincing evidence on the direct effect of public subsidies on R&D and fixed investment is an important issue since both types of firm activities are found in the literature to be major determinants of firm innovation activities and ultimately of a country's growth prospects. Still, this evidence is not conclusive since it is the effect of subsidies on innovation outputs—as opposed to innovation inputs—what matters the most. The ability of incentive schemes to allocate funds to the highest return projects should clearly be at the center of the literature, but there is still little direct evidence on this issue. More specifically, we do not know much about the effect of public subsidies on the pace of technological progress, although the role of intermediaries—including public bodies—in selecting entrepreneurs with the best chances of introducing new products or processes is a key mechanism through which GDP growth is affected.

In this paper we contribute to this infant literature by providing empirical evidence on the impact of state aids on innovation through the increased incentives to invest in R&D

¹See, for instance, the emphasis that the European Union put on innovation as an engine for growth in the context of the so-called Lisbon strategy launched in March 2000.

²The Oslo Manual (OECD, 1992, 1996, 2005) defines precisely what is meant by innovation and provides a taxonomy of ways in which a firm can innovate.

and fixed investment. To this end it is required, as it is not done in the existing literature, that we model both the relationships between each type of innovation output and innovation inputs and the relationships between each innovation input and (a combination of) state aid types.³ We do so by using various waves of a rich survey on innovation at the firm level gathered by Unicredit's Research Department for a large number of Italian firms.⁴ This survey contains detailed categorical information on the introduction of process, product and organizational innovation. Moreover, it contains quantitative information on inputs of the innovation process at the firm level, such as R&D spending and fixed investment, and on the way they are financed. In particular, we know whether a firm has benefitted from grants, tax credits or soft loans to finance R&D or fixed investment, and also the contribution of each type of aid on total financing. Available information preclude us from focussing on specific incentive programs as it is usually done in the so-called "program evaluation" literature. Since one of the objectives of this paper is indeed to throw some light on how firms exploit multiple state aid opportunities and on how this affects innovation outputs this is not a limitation.

From a methodological point of view our empirical approach requires the estimation of three sets of equations, each posing difficult econometric challenges. Compared to the vast majority of existing literature, an important advantage of the data set we use is that we have repeated cross-sections which allow us, in principle, to control for the firm specific and time invariant component of the error term and to avoid—at least partly—the standard endogeneity problems brought about by the non-observability of managerial quality. An additional econometric problem is that the identification of causal effects without making independency assumptions between firm level unobserved heterogeneity and the covariates requires lack of correlation between the regressors and the idiosyncratic error term at all leads and lags. This strict exogeneity assumption rules out the possibility that current values of some of the explanatory variables are correlated with present and past idiosyncratic errors. This is unlikely to be the case in the present context since, for instance, a firm level technology shock might be correlated both with R&D and fixed investment and with the probability of applying for and obtaining a public subsidy. Given the structure of our database, and indeed of most existing data-sets, there is no way of addressing this second concern in a fully satisfactory way.⁵ We address these issues by estimating an "expected subsidy" variable as a function of firm's observable characteristics. According to our main identifying assumption such a variable is exogenous in the R&D and fixed investment equations.⁶

³See Czarnitzki and Licht (2006) and Czarnitzki, Ebersberger and Fier (2007) who focus on patent activity, Hussinger (2008) on new product sales and Bérubé and Mohnen (2009) on a number of variables proxying for product innovation.

⁴This data set has been previously used for studying the effect of innovation on productivity (See Parisi, Schiantarelli and Sembenelli, 2006) and the effect of financial development on innovation (Benfratello, Schiantarelli and Sembenelli, 2008). To the best of our knowledge, however, information on public subsidies have not been exploited in depth yet.

⁵This is the case because only a very limited number of firms is present in all three consecutive waves we consider. This, for instance, makes the application of the standard GMM - first difference approach practically unfeasible.

⁶An economic model consistent with this approach is presented in González, Jaumandreu and Pazò (2005).

This paper is organized as follows. Section 2. provides a brief and selective review of existing literature. In section 3., we describe the data set we use for our investigation and we present some empirical regularities on public subsidies, R&D and fixed investment, and innovation in our sample. Section 4. presents some preliminary informative results on the relationship between R&D/fixed investment and various types of public subsidies. Section 5. is the core of our paper and contains our main empirical analysis. In particular section 5.1 presents evidence on the impact of investments on the innovation output; section 5.2 explains in detail how we address the main economic/econometric problem under analysis and section 5.3 comments upon the results. Section 6. concludes the paper by summarizing the results and describing the additional questions that could be addressed in future research.

2. Related Literature

Our paper contributes—albeit not exclusively—to the vast empirical literature which aims at assessing the effect of public subsidies on firm R&D and fixed investment. As noted by Ientile and Mairesse (2009) in their extensive review on the effects of R&D tax policies, the crucial issue in all this literature is the absence of a directly observable counterfactual, since the implementation of an experiment would imply that only some randomly selected firms receive the subsidy. This research strategy is not feasible in most industrialized countries since it distorts competition and therefore violates competition law. In turn, this presents a serious challenge to econometric analysis since in a standard investment equation the received subsidy is clearly endogenous. This is because of simultaneity and selection bias in the observed funding process or because there are omitted variables which are potentially correlated both with the decision of undertaking R&D activities and with the decision of applying to and obtaining a public subsidy.

David, Hall and Toole (2000) survey the older literature on the impact of public R&D firm subsidies on private R&D expenditures and conclude that at that time selectivity of funded firms into public funding was largely ignored. A useful way to provide a brief but informative review of the more recent literature is therefore to use as organizing principle a simple taxonomy of the different methodologies used to tackle the above mentioned econometric issues. The methods employed include non-parametric matching, difference-in-difference estimator, control function approaches (selection models) and IV estimation.⁷ All of these methodologies have advantages and disadvantages and the choice of the “appropriate” econometric method very often turns out to depend—over and beyond researchers’ idiosyncratic preferences— on the data-set on which it is applied. Data on R&D and innovation, including public subsidies, are commonly taken from innovation surveys which are of a cross-sectional nature. As a matter of fact it is always very difficult to address endogeneity issues and therefore make sensible statements on the directions of causality with cross-sectional data. Many of the relevant variables in innovation surveys concern firm strategic decisions: doing R&D, introducing innovation and applying for financial support. All

⁷To save on space we confine ourselves to the international literature which focuses on R&D investment and innovation. Most of the comments apply to the empirical literature on fixed investment as well.

these decisions are determined simultaneously and are jointly dependent on unobservable factors. Furthermore, only rarely we have variables which can be used as valid and relevant instruments. In principle, significant steps forward could be achieved with panel data. It is however difficult to construct panel data samples by merging consecutive innovation surveys because they are not performed on a yearly basis and variables are often observed at different frequencies. Moreover, they are typically based on a stratified sample design with dimensions that are relevant to the economic question addressed. This in turn might induce selectivity in the sample that may be differential overtime.⁸

The pioneering study by Wallsten (2000) investigates the effect on private R&D of the Small Business Innovation Research (SBIR) program implemented in the US. To address the endogeneity problem, he implements a small system of equations in which the endogenous award variable is instrumented with a variable proxying for the funds that are potentially awardable to the firm. He finds evidence that the grants crowd out firm-financed R&D spending dollar per dollar. Busom (2000) addresses the same economic issue by using a cross-section of Spanish firms conducting R&D activities. She addresses the problem of selection bias by applying a two-stage control function approach. In the first stage, she estimates a binary response model on the participation probability in public funding programs. In the second stage, the R&D activity is regressed against a set of covariates which include a selection term capturing differences in firm propensities to have access to public funds. The main finding of this paper is that public funding induces more private effort even if for some firms full crowding out effects cannot be ruled out.

Lach (2002) is the first paper to apply a conditional difference-in-difference (DID) strategy to analyze the effect of public subsidies on R&D expenditures. This was made possible by the availability of a longitudinal data-set collecting information on a sample of Israeli's R&D active firms per year. This methodological approach handles the problem caused by the likely fact that more successful firms might receive more R&D subsidies and do more R&D, provided that managerial quality is roughly constant during the sample period and it is therefore differenced out in the DID estimator. This estimator however is biased for the parameter of interest when obtaining a public subsidy is associated with unobserved idiosyncratic technology shocks which also lead to more R&D expenditures. He finds evidence that R&D subsidies granted by the Israeli's Ministry of Industry and Trade greatly stimulated firm private R&D expenditures for small firms but had a negative—albeit not significant—effect on the R&D of large firms.

In a number of related papers Czarnitzki and various co-authors also focus on crowding-out effects and introduce to this literature the non-parametric matching approach previously applied extensively to the literature on the evaluation of active labor market policies. In particular, Almus and Czarnitzki (2003) use—albeit without fully exploiting the longitudinal dimension—three waves of the Mannheim Innovation Panel and investigate the average causal effect of all public R&D schemes in Eastern Germany by using firm level R&D intensity as potential outcome variable. Compared to the case in which no public funding is provided,

⁸Mairesse and Mohnen (2010) discuss in detail the characteristics of the data innovation surveys usually contain and the challenges they pose to econometric analysis.

they find that benefitting firms increase their R&D activities by four percentage points. In a following paper, Czarnitski and Licht (2006) question whether this additional innovation input induced by public policy fosters innovation output, as measured by patent applications for both Eastern and Western Germany. In fact, as they correctly point out, it might well be possible that R&D public subsidies could also be spent inefficiently or alternatively be invested in extremely risky projects and therefore not to lead to an increase in output. They find a large degree of additionality both in innovation inputs measured as R&D or innovation expenditures and in innovation output as measured by the propensity to patent and the number of patent applications. Finally, Czarnitski, Ebersberger and Fier (2007) investigate whether R&D public subsidies and R&D cooperation affect both R&D and patenting activities using a sample of Western German and Finnish firms extracted from national Community Innovation Surveys (CIS). They consider the receipt of public subsidies and the participation to R&D cooperative efforts as heterogeneous treatments in order to be able to disentangle the two effects. The main conclusion they draw from their analysis is that in Finland both firm subsidies and cooperation activities have a positive impact on treated firms. In Germany, however, only cooperation and the combination of public subsidies with cooperative activities show significant effects.

González, Jaumandreu and Pazò (2005) is somehow closer in spirit to our approach. The authors develop a static model of investment decisions in R&D when some government support is expected and test it against an unbalanced panel of Spanish manufacturing firms surveyed during the period 1990-99. In short, each firm is considered as a product-differentiated competitor which faces a downward sloping demand function. In this context, R&D activity enters as a demand shifter by enhancing product quality. Given the presence of set up costs of R&D projects, there is a profitability threshold under which firms find it optimal not to perform any research activity, since R&D costs are not fully recovered through additional sales. This decision can however change if expected subsidies reduce the cost of R&D. The same argument also explains why R&D performing firms take expected subsidies into consideration when choosing the optimal size of planned R&D expenditures. In practice, the authors estimate expected subsidies and use them in explaining R&D participation and R&D effort by applying econometric methods which deal with selectivity and endogeneity. The structural model allows the authors to establish to what extent firms would have not initiated projects had the subsidies not been given. Results suggest that subsidies stimulate R&D although most firms that receive subsidies would have performed R&D anyway. In addition they find no crowding out of private funds.

More recently, Hussinger (2008) analyzes the effect of public R&D subsidies on firms' private R&D investment and new product sales in German manufacturing. As in several previous studies reviewed so far, the underlying database is the Mannheim Innovation Panel (MIP). She applies parametric and semiparametric two-step selection models, which relax the standard normality assumption of the error term, and finds that the average treatment effect on the treated firms is positive when R&D investment per employee is chosen as the outcome variable. In addition, this result is robust to alternative choices of semiparametric estimators. Interestingly for the purpose of our paper, she also regresses a variable proxying

for product innovation, namely firm level new product sales, on both private R&D investment per employee and the average treatment effect, set to zero for firms that do not receive public subsidies. A parametric test does not reject the hypothesis of equal coefficients of private and publicly induced R&D investment. In turn this suggests that they are equally productive in terms of new product sales.

Aerts and Schmidt (2008) also test whether public R&D subsidies crowd out private R&D investment in Flanders and Germany by using two consecutive waves of the national Innovation Community Surveys (CIS). The main methodological innovation of their paper is that they check the robustness of their results to alternative estimation methods. Operationally, the authors first use a non-parametric matching estimator which they apply only to a cross-sectional sample. As it is well known, the disadvantage of this estimator is that it does not control for any form—both permanent and transitory—of unobserved heterogeneity. To address this legitimate concern, they also exploit the longitudinal dimension and apply a combination of the matching procedure and the difference-in-difference (DID) methodology, known as conditional difference-in-difference (CDID). They find that the crowding-out hypothesis can be clearly rejected since funded firms are significantly more research active compared to non-funded firms. Moreover, this applies to both countries and holds for both estimation strategy.

Finally, Bérubé and Mohnen (2009) is, to the best of our knowledge, the only published paper which focuses primarily on innovation output. This paper looks at the effectiveness of R&D grants by comparing innovation performance measures between firms that received R&D tax credits only and firms that received both R&D tax credits and R&D grants. Using a non-parametric matching estimator and data from the 2005 Survey of Innovation from Statistics Canada they find that using tax credits and grants is more effective than using tax credits only, since firms benefitting from both types of incentives are found to introduce more new products, to make more world-first product innovations and to be more successful in commercializing their innovations.

3. Data

The data-set we employ in the analysis consists of three waves which report the responses on a set of items asked to managers of a large sample of Italian manufacturing firms. For our purposes the data contain rich information on the amount of investments in R&D and fixed capital, whether the firm introduced a product and/or process innovation as well as the proportion of total cost related to R&D and fixed investment financed by state aids in the form of soft loans, tax credits and grants. The three waves contain information for the following time periods: 1998-2000, 2001-2003, and 2004-2006.

In each wave the sample is selected (partly) with a stratified method for firms below 500 workers, whereas firms above this threshold are all included. Strata are based on geographical area, industry, and firm size. It is not completely clear, however, that the stratification criteria have remained constant over time. Moreover, some firms are added to the sample outside the stratification criteria. This may explain—together with macroeconomic

fluctuations—why one observes a substantial variation in the average and median size of the firms included in the sample, which makes it unfeasible to use aggregate wave statistics to track the evolution of relevant variables at the economy level. The sampling procedure is as such that not all the firms are present in all of the three waves: new firms are sampled in the second and third wave and some leave the sample either in the second or third wave. Table 1 shows that out of the 10,588 firms for which we have information in at least one wave only 435 are present in all of the three waves. For 2,220 we have two consecutive data points. Firm size, as measured by sales is described in table 2, which shows that both average and median size have a large drop in the third wave.

Table 3 reports, separately for each wave, the percentage of firms investing in fixed and R&D capital. As it can be seen, this percentage is substantial for fixed capital (ranging from 72% to 91%) whereas there is a large percentage of firms which are not engaged in formal R&D activity: more than half of the firms show in fact zero R&D spending in most periods (ranging from 54.4% to 66.3%). This is hardly surprising given the structure of Italian manufacturing characterized by a large number of small firms operating in low-medium tech industries. The conditional distribution of investments is shown in table 4. What we observe is a steady decline over time in the average size of both investment types. This decline is, however, less pronounced if one looks at the quantiles of the empirical distributions. In particular, R&D conditional distributions look very similar over time whereas a mild decline is observed in all quantiles of the conditional distributions for fixed investment.

Our data-set provides unusually rich information on the type of state aid the firm benefitted from as well as the proportion of the investment financed by such a source. The questionnaire elicits self-reported information about three specific forms of incentives: soft loans, tax credits and grants. Table 5 reports the share of beneficiaries for both investment activities and by type of subsidy. Overall, the share of benefitting firms in our sample can be considered as substantial in all three waves even if one observes a large drop in the proportion of firms which obtained grants or tax credits in the third wave. This reduction is coherent with the aggregate fall in state aids granted by Italian authorities in the final years of our sample period, also as a consequence of fiscal policy tightening. Table 5 also shows that for what concerns the investments in fixed capital (top part of the table) many firms in the first and second wave used tax credits which is used more often than soft loans and grants. Grants are the most used type of state aid to finance investment in R&D in the first two waves whereas soft loans prevail in the third wave (bottom part of the table).

A virtue of our data is also to provide additional information on the amount of each source of state aid, which is usually not observed in comparable data-sets such as the Community Innovation Survey (CIS). Summary statistics on this issue are provided in table 6 which shows the substantial amount of variation in the share of investment funded with public subsidies. For example, in the first wave the share of fixed investment subsidized with grants ranges from 10% (first quartile) to 40% (third quartile). The availability of such detailed information also allows us to assess the extent to which firms benefit from different types of subsidies in the same time period. Relevant results are summarized in table 7 which reveals that many firms benefit from more than one instrument. For instance, in the

first wave 557 firms (out of 1,587) made use of a single instrument whereas 399 benefitted from multiple instruments when considering R&D and fixed investment jointly. Finally, as documented in tables 8-13, for any type of state aid and in all the periods we observe non trivial dynamic patterns in our data-set : the cells off-diagonal of the transitions matrix are non-empty. For instance of the firms who had received a grant to finance fixed investment in the first/second wave, 81.3% would not received such an aid in the second/third wave. Symmetrically, of the firms who had not receive a grant in the first period, around 10.2% would receive such an aid in the second/third wave. Clearly these statistics suggest the possibility to exploit the within firm variation to control for unobserved heterogeneity.

We also observe many firms introducing innovations. For example, as table 14 shows, 35% of the firms introduce a product innovation in 1998-00 and 44.7% introduce a process innovation in the same time period. From this table it is transparent how substantial the innovation process is in our data-set for all the three periods we have. Moreover, as it is the case for the event of receiving a public subsidy, we observe a lot of transitions as it is documented in tables 15-16. Once again, this is comforting, since it allows us to exploit the within-firm variation in our econometric exercise.

4. Preliminary Empirical Evidence

In this section we describe preliminary regression results. In particular we want to show how the event of receiving a subsidy is related to the amount of investments in fixed capital and R&D and to what extent this association is robust to different assumptions on the conditional distribution of the error term. With this purpose in mind, table 17 shows the results of various regressions of the log of investments in fixed capital and R&D ($lfixinv$ and $lrdinv$) on firm size (the log of sales) and dummies for whether the firm had access to grants to fixed investments and R&D ($dgrants$ and $drgrants$), to tax credits ($dfiscal$ and $drfiscal$) as well as soft loans ($dinterate$ and $drinterate$). In running these regressions we also included time dummies and, whenever appropriate, area dummies and industry dummies which are omitted from the table. These additional regressors capture aggregate shocks as well as industry-specific and geographical time-invariant effects. Column 1 and 3 show how in a simple pooled OLS regression state aids which are specific to a given type of investment are positively correlated to the latter. Under the implausible assumption that all the relevant sources of unobserved heterogeneity are included in the regressors the pooled OLS regression would yield consistent estimates of the impact of state aids on investments.⁹

A more satisfactory econometric model is implemented in columns 2 and 4. The "fixed" effect model allows for an arbitrary correlation structure between the individual effect and the regressors.¹⁰ This key endogeneity issue is addressed by applying the standard

⁹The same results holds when we consider a random effect model which, with respect to the OLS regression, takes into account the structure of the error term to improve on efficiency. The coefficients are similar to the ones we got in the OLS model. This method, however, is still based on the implausible assumption that the expected value of the individual effect is uncorrelated with each and every covariate.

¹⁰In this case the within group transformation eliminates the industry and area dummies.

within-group transformation which removes the individual effect. Our results somehow change in the sense that the parameters are less precisely estimated. However the same basic qualitative message arises: more firm incentives are associated with a greater amount of investments. In this case, however, the value of the estimates gets diminished by roughly 50%, thus empirically confirming the upper bias in the relevant parameters arising from the omission of the time invariant component of managerial quality.

Although these results are informative about the strength of the mechanisms we are analyzing, it is still quite possible that they overestimate the "true" effect since they do not take into account the likely correlation between the idiosyncratic component of the error term and state aids. Indeed, industry or firm specific technology shocks are likely to affect both R&D and fixed capital spending and the probability of applying to and obtaining a subsidy. A useful—albeit partial—step in the right direction is therefore to allow for industry specific time effects capturing the industry specific component of technology shocks. In order to do so we also included dummies interacting industry and time. These additional regressors are obviously not eliminated once we apply the within group transformation. As we can see from table 18 the results obtained in table 17 are robust to the inclusion of these additional regressors. It is then reasonable to conclude that the correlation of subsidies and industry specific shocks is not contaminating our previous results.

Taken at face value our results so far indicate that i) the sign of the correlations between firm subsidies and both fixed and R&D investment is positive thus according to the favorable view of the role of public subsidies in stimulating investment, ii) the estimates of the impact of state aids on investments in R&D and fixed capital inflates the impact of state aids if we do not take into account the correlation between unobserved heterogeneity and the aids themselves, iii) controlling for industry specific technology shocks does not change our baseline results in a significant way.

It is still possible, however, that the error term is correlated with public subsidies, even after applying the within group transformation and controlling for industry-specific technology shocks. For instance, if a new engineer is hired by a firm and this expands the idiosyncratic technological opportunities of the hiring firm, its incentives both to invest and to apply to public subsidies are likely to be fostered. In order to address this remaining legitimate concern, we develop a simple econometric framework in the next section in which firm decisions on fixed and R&D new capital are taken as a function of an observable proxying for expected subsidies. This variable is assumed to be orthogonal to the error term and identification is achieved only through functional form assumptions. To make our approach manageable we aggregated the different kinds of state aids into a single binary variable: aid-no aid. Clearly in doing so we lose important details which are specific to our dataset. For this reason, in the next section we will not be able to provide additional information on the interplay of different instruments when applied to the same type of investment.

5. Econometrics

In order to address the main issue of this paper, namely the impact of state aids on innovation, we need to estimate two sets of parameters related to two types of relationships. First, we need to estimate two innovation production functions, which relate investments of different types to the probability of introducing a product or a process innovation. In this context the parameters we estimate have a clear economic interpretation in terms of marginal productivity of the inputs we measure. Second, we need to estimate the relationships which map state aids into the amount of R&D and fixed investment decided by the firm.

In both cases we have to face several difficult endogeneity problems. In particular, the estimation of innovation production functions requires to take into account the endogenous nature of the inputs which may be correlated both with unobserved heterogeneity and with the idiosyncratic component of the error term. The former can be thought in terms of firm unobservable characteristics which are not time-varying, e.g. managerial ability, while the latter as random opportunities which make innovation less or more profitable. In principle, the longitudinal aspect of our data-set allows us to take care of the first component by applying the conditional logit estimator. The price one has to pay is that only switchers contribute to the likelihood and this in turn can affect precision in a substantial way. The second task is much more difficult, also because of the discrete nature of our dependent variables. Even in a more standard linear framework, however, it would not be obvious how to solve this problem in a fully satisfactory way given the short dimension of our panel and the unavailability of convincing external instruments.

We also face similar endogeneity problems when we estimate the investment equations: in fact the amount of state aids is likely to be correlated both with the unobserved heterogeneity component and the idiosyncratic part of the error term. The approach we take here is to model the investment decisions as a function of expected subsidies, to estimate this expectation as a function of observables and to state and discuss explicitly the identifying assumptions underlying this estimation strategy.

5.1 Innovation Equations

We estimate binary response equations with logistic errors which are described by the following latent index models:

$$Y_{pit}^* = \alpha_{1f}I_{fit} + \alpha_{1r}I_{rit} + \alpha_{3p}(I_{fit} * I_{rit}) + \mathbf{Z}'_{it}\beta_p + u_{pit} \quad (1)$$

$$Y_{sit}^* = \alpha_{2f}I_{fit} + \alpha_{2r}I_{rit} + \alpha_{3s}(I_{fit} * I_{rit}) + \mathbf{Z}'_{it}\beta_s + u_{sit} \quad (2)$$

where we denote by Y_{pit}^* and Y_{sit}^* the level of product/process innovation introduced at time t by firm i , by I_{fit} and I_{rit} the amount of investment in fixed and R&D capital, while \mathbf{Z}_{it} is a set of explanatory variables for firm i at time t and u_{kit} is a shock to investment of type k at time t for firm i . The vector \mathbf{Z}_{it} includes firm size as measured by the log of sales in period t as well as industry and area dummies. The error term is decomposed into two parts: $u_{kit} = \omega_i + \varepsilon_{kit}$, $k \in \{p, s\}$, where ω_i captures the firm's managerial

ability while ε_{kit} represents a random i.i.d. shock which is assumed to be drawn after the investment decisions are made. Because of the discrete nature of the observed dependent variable it would be difficult to relax the assumption on the timing of the investment while also allowing for unobserved heterogeneity. In principle, however, it is possible that the amount of investment is related to a random opportunity which is incorporated in ε_{kit} and unobserved by the econometrician. We regard this identifying assumption as a limitation of our study. Furthermore, it would be reasonable to include in equations (1) and (2) as regressors also the lagged investment variables to capture state dependency as typically done in the dynamic panel data literature. Under fairly general assumptions it would be possible to consistently estimate the parameter attached to this additional regressor without having to rely on a random effect approach. "Fixed" effect estimators such as the ones developed by Honorè and Kyriazidou (2000) and Bartolucci and Nigro (2010) would accomplish this task. However, the first estimator would need at least four data points while the second could in principle be implemented with three data points while having to deal with some interpretation issues¹¹.

The three columns of table 19 show the result of logistic regressions for product innovation using the pooled data (first column), adopting a random effect approach (second column) and a "fixed" effect approach (third column).¹² In running these regressions we included wave dummies and, where appropriate, industry and area dummies. The results of columns 1 and 2 are coherent with an optimistic view of the role of public subsidies: both investment in R&D and in fixed capital have a positive impact on the probability of introducing an innovation. When computed at the mean, the marginal effect is equal to 0.051 for R&D and to 0.027 for fixed investment in column 1. These two inputs also appear to be substitutes.¹³ Moreover firm size, whose proxy is the log of sales, has a negative impact. This might reflect inefficiencies which in bigger firms, everything else being the same, slow down the innovation process. When we adopt a "fixed" effect model, that investments of both types positively affects the probability of introducing a product innovation is less clear since the relevant coefficients are estimated less precisely. However the same qualitative message results from the third column.¹⁴

The results for an analogous exercise for process innovation are described in table 20. Also in these regressions we included wave dummies and, whenever appropriate, industry dummies and area dummies. The qualitative results are similar to the ones for product innovation. As it can be seen from columns 1 and 2, both types of investment have a positive impact on the probability of introducing a process innovation. When computed at the mean,

¹¹In absence of a fully specified economic model the interpretation of the estimates for our application would indeed be problematic.

¹²Robust standard errors are in round brackets.

¹³As it is well known, in non-linear models the interaction coefficient α_{3k} does not measure the cross-partial derivative of interest. This implies that the sign of α_{3k} does not necessarily indicate the sign of the interaction effect (see Ai and Norton, 2003). When computed correctly the full interaction term is negative and statistically significant for many observations. The average effect is equal to -0.007 and the corresponding average standard error is equal to 0.003.

¹⁴The lower precision of the estimates may be due to the fact that the sample size reduce from 2,786 to 203 observations since only switchers contribute to the likelihood.

the marginal effect is equal to 0.035 for R&D and to 0.036 for fixed investment in column 1. Moreover there appears to be also in this case some degree of substitution between the two types of investment.¹⁵ As for product innovation, the results in the case of the "fixed" effect logit are less striking. As it can be seen from column 3 of table 20 the parameters maintain their signs but are less precisely estimated.

Overall this set of results is coherent with our approach. Both fixed and R&D investment are found to be important factors in explaining both process and product innovation—albeit in different proportions. When assessing the effect of public subsidies on innovation output it is therefore crucial to analyze the effect of both fixed and R&D investment subsidies, since they both might affect innovation output to the extent that they contribute to fostering their targeted innovation inputs.

5.2 Expected Aids

In order to deal with the endogenous nature of the public subsidies received by the firm we assume that the decisions to invest in R&D and fixed capital are based on the expected fractions of the investment the firm believes will be financed by the government (g). Moreover we also assume that such state variables are related to observable firm characteristics through a known functional form. The definition of expected subsidies implies that $\mathbb{E}[g] = \Pr(g > 0)\mathbb{E}[g|g > 0]$. Therefore we need to model both the probability of receiving a public subsidy as well as its expected size. Moreover, in our case this needs to be done both for the investment in R&D and for the investment in fixed capital.

In practice we relate these two objects to firm characteristics—assumed to be exogenous—which may enhance firm eligibility and/or willingness to apply. These include firm size ($\ln sales$) and age (age), dummies for legal status ($legal$), group ($group$) and consortium ($consortium$) membership and the quality of the workforce as measured by the share of workers with a high-school degree or more ($education$). Following Gonzàles, Jaumandeu and Pazò (2005) we also include three additional variables with the purpose of capturing granting agency preferences: an export dummy ($exporter$) and two variables which proxy for the firm's geographical market ($geomarket$) and the average size of the competitors ($compsize$). In all estimated equations we also include wave, area and industry dummies.

As already mentioned in the previous section and in order to efficiently use our data and have enough observations to make the described approach feasible we aggregated the information on the type of state aid received by the firm. Thus we have a binary variable which takes the value of one if the firm received a grant and/or a soft loan and/or a tax credit and zero otherwise. In order to construct the expected subsidy variable we first model the probability of receiving an aid ($\Pr(g > 0)$) in terms of a logit model. The first column in table 21 shows the results for the probability of receiving an aid to fixed investment while the second for the probability of receiving an aid to R&D investment. The coefficients attached to wave dummies, industry dummies and area dummies are omitted. Except for the average competitor size variable, the education level and the export dummy, all other covariates

¹⁵The average interaction effect is equal to -0.008 with an average standard error of 0.003.

are statistically significant in at least one of the two equations. Being large, belonging to a consortium and facing international competition are all factors which enhance the probability of obtaining a subsidy both to fixed and R&D investment. Belonging to a group and having limited liability decrease instead the probability of obtaining an aid to fixed investment. We use these estimates to predict the probability that the firm will receive a subsidy of a given type and we denote the prediction as \hat{p} .

The second step to compute $\mathbb{E}[g]$ requires that we regress the (log of the) share of investment which is financed by some kind of aid on the same firm characteristics. Therefore, we model $\mathbb{E}[g|g > 0]$ as a linear function of the same set of covariates: firm size and age, legal status, dummies for whether the firm belongs to a group or to a consortium, the education level of the employees, export status, geographical market size and the average competitor size. As usual, wave, area and industry dummies are also included. The results are presented in table 22 where we omit industry, time and area dummies to save on space. We can see that the share of investments financed by the government is negatively correlated to firm size. The latter is in fact the only significant regressor for the amount received for R&D investment, in addition to some of the dummies we omitted from the table. On the contrary, belonging to a group and facing international competition has a negative impact on the amount received for investments in fixed capital whereas the education level has a positive effect. Following Gonzàles, Jaumandeu and Pazò (2005) we use the estimates in table 22 to predict $\mathbb{E}[g|g > 0]$. By exploiting log-normality, we then compute the expected subsidies as follows: $\hat{\rho}^e = \hat{p} \exp(\mathbf{Z}'\hat{\lambda} + 1/2\hat{\sigma}^2)$, where $\mathbf{Z}'\hat{\lambda}$ is the forecasted share of investment financed by the government.

5.3 Investments Equations and R&D Participation Decision

We denote by $\hat{\rho}_f^e$ and $\hat{\rho}_r^e$ the predicted share of investment financed by public subsidies in fixed and R&D capital respectively. In order to assess if state aids have an impact on firm investment behavior we regress both whether or not to invest (extensive margin) and how much (intensive margin) on $\hat{\rho}_f^e$ and $\hat{\rho}_r^e$ as well as on the same set of covariates entering as explanatory variables in the equations commented upon in section 5.2. Because most of the firms in our sample perform investment in fixed capital we only analyze the fixed investment effort decision. Table 23 reports the result of OLS regressions using the pooled data of the log of investments in R&D and fixed capital on $\hat{\rho}_f^e$ and $\hat{\rho}_r^e$ (columns 1 and 3). We also replaced the expected subsidy variables with the corresponding predicted probabilities of receiving a grant (\hat{p}_f and \hat{p}_r), that is the first components in the expression for $\hat{\rho}_f^e$ and $\hat{\rho}_r^e$. This additional set of results is reported in columns 2 and 4. We do so since we are not fully comfortable with our model ability to predict conditional expected subsidies out-of-sample, particularly for the R&D investment case where the sample size is relatively small. Providing indirect evidence that the effects we might find are not sensitive to potential prediction fallacies is therefore an important addition to the credibility of our estimation strategy.

The main results reported in table 23 can be summarized as follows. Firstly, the effect

of an increase in the predicted probability of receiving a R&D subsidy on R&D investment is positive and significant (column 2). Also the effect of an increase in the size of expected R&D subsidies is positive albeit not significantly different from zero at conventional statistical levels (column 2). Secondly, both the effect of an increase in the probability of receiving a fixed investment aid (column 4) and the effect of an increase in the expected size of such a subsidy (column 3) are positive and significant.¹⁶ Thirdly, larger firm invest more as one would probably expect and the same is true for firms that belong to a group. Both results are consistent with the existence of financial constraints which are more likely to hit small firms and/or firms which cannot benefit from an internal capital market.

Finally, we also seek to explain the decision to engage into R&D activities (extensive margin) by running an analogous set of regressions. The results of pooled logit estimates are presented in table 24. The results indicate that both $\hat{\rho}_R^e$ and \hat{p}_R do not increase the propensity to conduct R&D activity. Although the parameters are not significant at conventional statistical levels their negative signs are hard to interpret. It would then seem that government intervention does not have an impact on the extensive margin: firms would perform R&D activity regardless of the expected amount of aids received and of the likelihood to receive such an aid.

6. Conclusions

In this paper we set ourselves the ambitious objective of building a sufficiently general empirical framework which allows the joint analysis of the effects of both R&D and fixed investment subsidies on two different types of innovation outputs, namely product and process innovation. In doing so we complement the existing literature which so far has focussed almost exclusively on the effect of R&D subsidies on R&D spending and, in a limited number of papers, on product innovation. In our view this is a major shortcoming since it is now commonly recognized that innovation comes in many different forms and that R&D is only one—albeit obviously crucial—element of the innovation production function.

Our work provides three pieces of evidence which are consistent with this view. Firstly, we provide robust descriptive evidence that show that different types of subsidies are positively correlated with fixed investment and R&D spending even after allowing for individual effects and controlling for industry specific technology shocks. We do not go so far as to give these preliminary findings a causal interpretation despite the fact that this approach controls for firm unobservables which remain constant over the sample period.

Secondly, both R&D and fixed investment are found to affect the probability of introducing product as well as process innovations. The first obvious implication of this finding is that there is something to be learnt in going over and beyond R&D subsidies when assessing the effect of firm subsidies on innovation outputs. The second, possibly less obvious,

¹⁶We also run "fixed" effect models for both R&D and fixed effect investments. We found a positive and significant impact of \hat{p}_f and \hat{p}_r , but a negative impact of $\hat{\rho}_f^e$ and $\hat{\rho}_r^e$, the latter also being marginally significant. As of now we do not have a clear intuition to justify signs associated to the second set of regressors. More analysis is warranted to clarify this finding.

implication is that different types of innovation show different responses to different inputs. In this paper we indeed find that the marginal productivity of R&D on product (process) innovation is higher (lower) than the marginal productivity of fixed investment. Therefore, not only we have to take into consideration different types of subsidies but also the fact that they may affect differently different types of innovation outputs.

The third contribution of our paper is to provide an econometric framework which allows to take all these elements into consideration into a coherent and tractable way. Obviously, assessing public policies towards firms remains an extremely challenging exercise for a variety of reasons including the impossibility of running randomized experiments and the difficulties in measuring innovation and in collecting the relevant data over time in a consistent way. Still, by exploiting publicly available data we have been able to address some of the standard endogeneity concerns which plague this empirical literature. Finally, taken at face value and not without some qualification, our results suggest that firm subsidies affect innovation outputs through their role in enhancing innovation inputs.

7. References

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Table 1: Panel Structure

Dep. Var.	No. of Firms	Frequencies
Only third wave	3,783	35.7
Only first wave	2,327	22.0
Only first and second waves	1,640	15.5
Only second wave	1,591	15.0
Only second and third waves	580	5.5
All the waves	435	4.2
Only first and third waves	232	2.1
Total	10,588	100.0

Table 2: Triennial Sales in Million Euros

	1998-00	2001-03	2004-06
Number of Firms	4610	4,005	5,026
Mean	71.7	89	56.3
Std. Deviation	188.7	203.3	147.6
1st Quartile	12.2	12.9	8.9
Median	21.4	29.4	16.7
3rd Quartile	46.5	67.1	39.8

Table 3: Firms with Positive Investment Spending

	Fixed Investment (FI)		R&D Investment	
	Obs	Obs with FI>0	Obs	Obs with R&D>0
1998-00	4,634	91.0 %	4,572	37.7 %
2001-03	4,242	85.9 %	4,136	45.6 %
2004-06	5,030	72.0 %	5,030	33.7 %

Table 4: Triennial Fixed and R&D Investment in Million Euros (Conditional on Non-zero Investment)

	Fixed Investment			R&D Investment		
	1998-00	2001-03	2004-06	1998-00	2001-03	2004-06
Number of Firms	3,376	3,334	1,901	1,396	1,473	1,696
Mean	3.8	2,6	2.1	1.8	1,2	0.7
Std. Deviation	11.4	5.9	5.3	7.5	3.3	1.6
1st Quartile	0.3	0.2	0.1	0.1	0.1	0.1
Median	0.9	0.6	0.6	0.3	0.3	0.2
3rd Quartile	2.5	2.2	1.9	0.9	0.9	0.6

Table 5: Share of Benefitting Firms

	1998-00	2001-03	2004-06
Fixed Investment			
No. of Firms with Available Financial Data	4,154	3,465	3,203
Grants	16.3 %	16.4 %	2.3 %
Tax Credits	24.4 %	18.5 %	3.3 %
Soft Loans	11.8 %	15.2 %	14.9 %
R&D Investment			
No of Firms with Available Financial Data	1,662	1,806	1,326
Grants	15.5 %	18.2 %	5.1 %
Tax Credits	13.3 %	9.9 %	5.1 %
Soft Loans	5.7 %	6.2 %	13.9 %

Table 6: Share of Subsidies on Total Financing (%)

	1998-00			2001-03			2004-06					
	No.	1st Q	2ndQ	3rd Q	No.	1stQ	2ndQ	3rdQ	No.	1stQ	2ndQ	3rdQ
Fixed Investment												
Grants	678	10	20	40	569	8	10	30	72	10	25	50
Tax Credits	1014	10	20	34	642	8	15	30	106	20	25	40
Soft Loans	492	20	43	70	527	20	40	60	477	30	50	100
R&D Investment												
Grants	257	10	30	50	328	10	20	50	68	15	30	50
Tax Credits	221	10	25	50	178	10	20	50	67	15	50	80
Soft Loans	94	20	47	80	112	20	50	80	184	50	100	100

Table 7: Types of instruments (Conditional on Non-zero Investment)

	1998-00			2001-03			2004-06		
	Fix Inv	R&D Inv	Tot	Fix Inv	R&D Inv	Tot	Fix Inv	R&D Inv	Tot
No. of Firms	4,154	1,662	1,587	3,465	1,806	1,659	3,203	1,326	959
0 Instrument	2,349	1,171	631	2,087	1,256	753	2,589	1,036	637
1 Instrument	1,460	420	557	1,066	481	527	579	270	232
2 Instruments	311	61	283	264	61	268	29	11	74
3 Instruments	34	10	80	48	5	60	6	9	13
>3 Instruments			36			51			3

Table 8: Transitions in fixed investment (FI) grants

		grants W2/W3		
grants W1/W2	0	1	Total	
0	1,938	221	2,159	
percentage	89.76	10.24	100.00	
1	373	86	459	
percentage	81.26	18.74	100.00	

Table 9: Transitions in FI tax exemptions

		fiscal W2/W3		
fiscal W1/W2	0	1	Total	
0	1,784	205	1,989	
percentage	89.69	10.31	100.00	
1	508	121	629	
percentage	80.76	12.45	100.00	

Table 10: Transitions in FI subsidized rate aids

		interate W2/W3		
interate W1/W2	0	1	Total	
0	2,016	220	2,236	
percentage	90.16	9.84	100.00	
1	316	66	382	
percentage	82.72	17.28	100.00	

Table 11: Transitions in R&D grants

		grants W2/W3		
grants W1/W2	0	1	Total	
0	770	101	871	
percentage	88.40	11.60	100.00	
1	175	51	226	
percentage	77.43	22.57	100.00	

Table 12: Transitions in R&D tax exemptions

		fiscal W2/W3		
fiscal W1/W2	0	1	Total	
0	898	49	947	
percentage	94.83	5.17	100.00	
1	130	20	150	
percentage	86.67	13.33	100.00	

Table 13: Transitions in R&D subsidized int. rate aids

		interate W2/W3		
interate W1/W2	0	1	Total	
0	967	56	1,023	
percentage	94.53	5.47	100.00	
1	64	10	74	
percentage	86.49	13.51	100.00	

Table 14: Number of Innovative Firms

	1998-00		2001-03		2004-06	
	No.	%	No.	%	No	%
Product Innovation	1,147	35.0	1,732	53.8	2,47	52.0
Process Innovation	1,721	44.7	1,769	54.3	2,145	45.1

Table 15: Transitions in product innovation

		prod. innovation W2 W3		
prod. innovation W1	W2	0	1	Total
0		657	443	1,100
percentage		59.73	40.27	100.00
1		317	691	1800
percentage		31.45	68.55	100.00

Table 16: Transitions in process innovation

		proc. innovation W2/W3		
proc. innovation W1/W2		0	1	Total
0		667	420	1,087
percentage		61.36	38.64	100.00
1		482	720	1202
percentage		40.10	59.9	100.00

Table 17: Regressions of Investments on Firm Subsidies with Aggregate Time Dummies

Method	Pooled OLS (1) lfixinv	"Fixed" Effect (2) lfixinv	Pooled OLS (3) lrdinv	"Fixed" Effect (4) lrdinv
lsales	0.863*** (0.012)	0.447*** (0.103)	0.724*** (0.017)	0.344** (0.165)
dgrants	0.489*** (0.041)	0.217*** (0.069)***		
dfiscal	0.408*** (0.036)	0.209*** (0.064)		
dinterate	0.323*** (0.040)	0.187** (0.080)		
drgrants			0.624*** (0.056)	0.263** (0.110)
drfiscal			0.460*** (0.068)	0.205* (0.122)
drinterate			0.093 (0.072)	0.330** (0.156)
constant	-2.979*** (0.257)	1.570 (1.048)	-1.401*** (0.308)	2.081 (1.716)
N	8119	8119	4214	4214

Robust standard errors in round brackets

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Regressions of Investments on Firm Subsidies with Industry Specific Time Dummies

Method	(1)	(2)	(3)	(4)
	Pooled OLS lfixinv	"Fixed Effect" lfixinv	Pooled OLS lrdinv	"Fixed Effect" lrdinv
lsales	0.865*** (0.012)	0.554*** (0.099)	0.724*** (0.017)	0.348** (0.169)
dgrants	0.492*** (0.041)	0.223*** (0.069)		
dfiscal	0.409*** (0.036)	0.213*** (0.065)		
dinterate	0.319*** (0.040)	0.185** (0.081)		
drgrants			0.603*** (0.056)	0.202* (0.112)
drfiscal			0.443*** (0.068)	0.167 (0.119)
drinterate			0.089 (0.072)	0.333** (0.156)
constant	-2.933*** (0.268)	1.062 (1.046)	-1.426*** 0.324	1.838 1.039
N	8119	8119	4214	4214

Robust standard errors in round brackets

Wave, industry and area dummies are omitted

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Probability of Introducing a Product Innovation

Dep. Var.	innoprod	innoprod	innoprod
Method	Pooled Logit	RE Logit	Cond. Logit
log(fixinv)	0.297(0.089)	0.321(0.102)	0.606(0.413)
log(rdinv)	0.459(0.100)	0.492(0.120)	0.753(0.420)
log(fixinv)log(rdinv)	-0.029(0.014)	-0.031(0.016)	-0.072(0.060)
log(sales)	-0.168(0.052)	-0.180(0.059)	0.112(0.514)
N	2786	2786	203

Robust standard errors in round brackets

Wave, industry and area dummies are omitted

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Probability of Introducing a Process Innovation

Dep. Var.	innoproc	innoproc	innoproc
Method	Pooled Logit	RE Logit	Cond. Logit
log(fixinv)	0.389(0.092)	0.406(0.104)	0.559(0.410)
log(rdinv)	0.419(0.102)	0.436(0.116)	0.691(0.453)
log(fixinv)log(rdinv)	-0.033(0.014)	-0.035(0.016)	-0.077(0.066)
log(sales)	-0.096(0.051)	-0.100(0.054)	0.986(0.843)
N	2788	2788	210

Robust standard errors in round brackets

Wave, industry and area dummies are omitted

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Probability of Obtaining a Subsidy - Pooled Logit Estimation

	(1)	(2)
	dfixaid	drdaid
lsales	0.186*** (0.024)	0.209*** (0.037)
age	-0.000* (0.000)	0.003 (0.002)
legal	-0.277** (0.123)	0.364 (0.289)
group	-0.221*** (0.066)	-0.103 (0.095)
consortium	0.407*** (0.077)	0.389*** (0.119)
education	-0.141 (0.099)	0.232 (0.159)
exporter	-0.052 (0.053)	0.041 (0.108)
geomarket	0.193*** (0.056)	0.295*** (0.083)
compsize	-0.010 (0.051)	-0.103 (0.081)
constant	-2.418*** (0.493)	-5.483*** (0.693)
N	8132	4444

Robust standard errors in round brackets

Wave, industry and area dummies are omitted

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: Share of Firm Subsidies Equations - Pooled OLS Estimation

	(1)	(2)
	lsfixaid	lsrdaid
lsales	-0.792*** (0.031)	-0.658*** (0.056)
age	-0.000*** (0.000)	-0.001 (0.003)
legal	0.017 (0.122)	-0.092 (0.381)
group	-0.283*** (0.073)	-0.151 (0.132)
consortium	0.008 (0.081)	-0.166 (0.157)
education	0.391*** (0.114)	-0.284 (0.224)
exporter	-0.097 (0.060)	-0.018 (0.160)
geomarket	-0.204*** (0.063)	-0.189 (0.118)
compsize	-0.018 (0.059)	-0.068 (0.116)
const.	5.593*** (0.475)	4.633*** (0.738)
N	2561	806

Robust standard errors in round brackets

Wave, industry and area dummies are omitted

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Investment Equations: Intensive Margins - Pooled OLS Estimation

	(1)	(2)	(3)	(4)
	lrdinv	lrdinv	lfixinv	lfixinv
$\hat{\rho}_r^e$	1.498 (0.916)			
$\hat{\rho}_f^e$			0.725** (0.353)	
\hat{p}_r		6.494*** (0.819)		
\hat{p}_f				5.232*** (1.079)
lsales	0.677*** (0.032)	0.415*** (0.038)	0.861*** (0.018)	0.645*** (0.046)
age	0.002 (0.001)	-0.001 (0.001)	0.001 (0.001)	0.000*** (0.000)
legal	0.095 (0.166)	-0.224 (0.169)	-0.110 (0.094)	0.204* (0.121)
group	0.243*** (0.060)	0.326*** (0.060)	0.178*** (0.042)	0.418*** (0.066)
consortium	0.014 (0.075)	-0.484*** (0.095)	0.079 (0.052)	-0.409*** (0.115)
education	0.436*** (0.099)	0.147 (0.103)	-0.330*** (0.068)	-0.173** (0.073)
exporter	0.054 (0.064)	0.052 (0.064)	0.110*** (0.036)	0.169*** (0.038)
geomarket	0.326*** (0.049)	-0.035 (0.066)	0.153*** (0.036)	-0.076 (0.061)
compsize	0.104** (0.048)	0.215*** (0.051)	0.056* (0.034)	0.066* (0.034)
consortium	-1.482*** (0.489)	1.492*** (0.528)	-2.499*** (0.317)	-2.904*** (0.314)
N	3073	3073	6452	6454

Robust standard errors in round brackets

Wave, industry and area dummies are omitted

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24: Investment in R&D: Extensive Margin - Pooled Logit Estimation

	(1)	(2)
	drdinv	drdinv
$\hat{\rho}_r^e$	-4.190 (2.892)	
\hat{p}_r		-2.872 (4.654)
lsales	0.203*** (0.067)	0.310*** (0.073)
age	0.005* (0.003)	0.005* (0.003)
legal	-0.634* (0.343)	-0.612* (0.349)
group	-0.034 (0.155)	-0.043 (0.157)
consortium	0.512 (0.341)	0.579* (0.357)
education	-0.064 (0.219)	-0.029 (0.232)
exporter	0.592*** (0.145)	0.602*** (0.146)
geomarket	0.363*** (0.137)	0.411** (0.169)
compsize	0.150 (0.123)	0.151 (0.127)
cons	2.492* (1.310)	1.874 (1.387)
N	2926	2926

Robust standard errors in round brackets

Wave, industry and area dummies are omitted

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$