The impact of science and technology parks on firms product innovation: empirical evidence from Spain

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25 February 2011

The impact of science and technology parks on firms´ product innovation: empirical evidence from Spain

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ABSTRACT

Science and Technology Parks (STP) are one of the most important and extensive innovation policy initiatives introduced in recent years. This work evaluates the impact of STP on firm product innovation in the Spanish context. Spain is less developed than most of the advanced countries, and regional and national governments are prioritizing STP initiatives. The large firm sample for our study is from the Spanish Technological Innovation Survey, provided by the National Statistical Institute. We focus on average treatment effects for firms located in 22 Spanish STP. Our results show that Spanish STP have a strong and positive impact on the probability and amount of product innovation achieved by STP located firms. These results hold for different assumptions about the mechanisms underlying location in a STP.

Keywords: Science and Technology Parks, product innovation, treatment effects, regional development policies.

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1. INTRODUCTION

The importance of science and technology parks (STP) is being underlined by policy makers who are devoting increased resources to these initiatives which are central to the regional development policies in many countries. The rise of these initiatives began in the 1980s and continued in the 1990s (Vestergaard et al., 2005), with their rapid expansion driven by institutional changes (e.g. legislation on the appropriation of research output) (Siegel et al., 2003b; Link and Scott, 2007). The objectives of policy makers were to construct an environment conducive to innovation and growth and to provide 'a perfect physical and social infrastructure which may attract high-tech firms ... by means of the establishment and upgrading of local institutions and networks in order to stimulate new ideas and technologies' (Lambooy and Boschma, 2001: 121-122).

This paper examines the case of Spain, a special case owing to the specific organizational development route followed. The first Spanish STP were established in the mid-1980s. They were an initiative within the Spanish regional development strategies and had no formal connections to central government or the universities. Their primary objective at that time was to attract large high-tech firms (especially multinational), which were seen as the key to economic and industrial development in the regions. After some years, parks attracted the attention of the university sectors, and several universities embarked on initiatives to set up small STP on or close to their main campuses, primarily to conduct R&D and provide a location for new technology based firms (NTBF). Recognition of the important role of universities in knowledge transfer motivated already established parks to establish or increase their connections to universities (Ondategui, 2001; Romera, 2003). STP in Spain began a period of expansion after 2000, officially supported by national government. Since then public actions to support STP in Spain have intensified resulting in an increased number of parks and in their being one of the main innovation policy initiatives being implemented in Spain.

Several academic works have investigated the impact of STP in various countries. They generally compare the performance of firms located inside and outside STP using various indicators. The evidence from these studies is mixed. We build on this literature in order to evaluate the impact of STP on product innovation in firms. We use data from the 2007 Spanish Technological Innovation Survey, managed by the National Statistical Institute (INE). Our study has some important features.

First, we rely on econometric methods to evaluate the causal effects of these initiatives to account for the fact that participants are not randomly selected or are not selected based only on observed characteristics. Existing work that evaluates the impact of STP usually does not consider the selection of firms based on unobserved aspects related to expectations about the benefits of location in a park. The present study employs several different methods, each involving a different set of assumptions, in order to account for selection and endogeneity problems. Use of a set of different methods also allows more robust conclusions.

Second, to our knowledge, this is the first time that a Community Innovation Survey (CIS)-type survey has been used to evaluate the impact of STP. This is an important feature of the present study in the sense that it allows us to study the influence of parks using indicators commonly used in innovation studies, such as percentage of firms` sales from new-to-the-market products. This indicator provides an economic measure of product innovation. We can control for the influence of other firm factors that have been tested extensively in the literature, and we have access to a much larger sample than in other STP evaluations. Our sample includes 39,722 firms, representative of the whole population of Spanish firms.

Third, we analyse the average performance of Spanish STP. Due to our large sample size, we are able to piece together a representative picture of the population of Spanish STP, based on firms from 22 of the 25 official Spanish STP.

Fourth, we focus on the Spanish case: previous work focuses mainly on the UK, the USA and Sweden,[e] and provides very little evidence for less developed contexts where STP might be especially important. See, for example, Sofoulli and Vonortas (2007) for Greece, and Colombo and Delmastro (2002) for Italy on the importance of parks in those contexts.

The paper is organized as follows. Section 2 reviews the theoretical foundations to park-type initiatives and the empirical studies on their impact. In section 3, we describe the econometric framework we use to estimate the impact of STP. Section 4 presents the data and variables and Section 5 discusses the results. Section 6 offers some concluding remarks.

2. PREVIOUS LITERATURE

We discuss the theoretical groundings of STP and empirical work on the impact of STP upon firms' results and behaviour.

2.1. Theoretical grounding of STP

Governments have become increasingly interested and active in creating conditions conducive to innovation through localized knowledge development and knowledge transmission mechanisms. These initiatives are supported theoretically by arguments highlighting the importance of location externalities for industrial development, the way that the intricate nature of the innovation process determines its spatial dimensions and the implications of agglomeration for innovation.

The importance of location for industrial development received much research attention in the 1980s and 1990s. The issue of location choice has been researched by urban and regional economists (see Mills, 1987 for a complete account), while economic geographers have provided enlightening case studies (e.g. Saxenian, 1994) showing how certain locations and institutional environments attract innovators. The idea of industrial districts (Marshall, 1920) and later industrial clusters (Porter, 1990; Krugman, 1991) promoted the notion that local competences influence firms when deciding about where to locate, and constitute advantages for firms. Empirical assessment of these claims is provided in Baptista and Swann (1998), which shows that firms located in strong clusters are more likely to innovate due to location externalities.

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[e] UK: Monck et al. (1988); Westhead and Storey (1994); Westhead (1997); Siegel et al. (2003a, 2003b); USA: Link and Scott (2003, 2006, 2007); Appold (2004);Sweden: Löfsten and Lindelöf (2001, 2002, 2003, 2005); Lindelöf and Löfsten (2003, 2004); Ferguson and Olofsson (2004); Dettwiler et al. (2006).

The process of innovation has been described as knowledge-fuelled, entailing uncertainty and facilitated by the interactions between knowledgeable agents (Nelson 2000; McKelvey, 1996). The uncertainty is related to the outcome of the innovation process, and induces firms to search locally for competences, for example, via localized networks of innovators (Baptista and Swann, 1998; Freeman, 1991). These local interactions have been found to be more durable than formal, international strategic alliances (DeBresson and Amesse, 1991; Baptista and Swann, 1998), a fact that perhaps might be explained by the path dependency and cumulativeness of the research process (Lambooy and Boschma, 2001). In other words, firms feel safer when building on what they already know or in seeking complementary knowledge from organizations located close to their research efforts. Hence, proximity and agglomeration of innovative effort, can provide a catalyst for the search for new technologies and new collaborations.

In general, would-be innovators need to invest in the production of new and recombinations of existing knowledge in order to introduce market novelties. The intangible nature of knowledge means that some of it will be appropriated and some will not and that knowledge externalities/spillovers will occur and that the returns from knowledge spillovers associated with R&D are likely to be geographically localized (Jaffe, 1986, 1989). The geographical containment of spillovers is generally explained by the features of tacit and codified knowledge. Tacit knowledge flows better locally than across huge distances (Pavitt, 1987; Maskell and Malmberg, 1999; Asheim, 1996) since it is transmitted through personal contact and the development of personal relations based on trust (Cooke and Morgan, 1998; Morgan, 1997).

The issue of knowledge spillovers and their geographical dimension has been translated into well grounded rationales for policy intervention. In considering interactive learning to be a source of innovation (Nelson, 1993; Lundvall, 1992), knowledge spillovers can be seen as creating inter-organizational learning effects (Metcalfe, 1994), and uncertainty can be seen as inducing agents to continue along existing research paths and to collaborate. Proximity facilitates all these features, and has been a focus for policy makers.

The literature on US and UK STP highlights a general trend towards the use of these and similar instruments, guided by the neoclassical view of knowledge spillovers as market failures leading to underinvestment, and a linear view of the innovation process. More specifically, STP have been seen as the means to correct market failure related to lack of financing for new firms based on the uncertain returns from investment in new technologies (Colombo and Delmastro, 2002; Siegel et al., 2003a), or the need to promote productivity and industrial development in locations that otherwise would underperform (Appold, 2004). STP were created on the assumption that technological innovation stems from basic research and that a park environment would facilitate the transformation of pure research into commercially exploitable products along a successive chain of activities (Westhead, 1997; Vestergaard et al., 2005; Siegel et al., 2003b). Similarly, the idea that ensuring supply of the physical and human infrastructure is a *sine qua non* for innovation has underpinned these policy actions. Based on this rationale, STP (especially those in the UK and US) represent a distinct and formal division of labour with regard to the expected output of participants, and the presence of a university and active participation of government authorities are prerequisites (Westhead and Storey, 1994).

On the other hand, some science and technology parks, especially in Europe, are looser structures of localized knowledge development and sharing activities. They are based on the innovation success of clusters and “innovative milieux” based on the local clustering of innovative actors with common territorial relationships incorporating a production system, a specific culture and a system of representation (Keeble et al., 1999). Collective learning processes involve the creation and development of a common heuristics among territorial agents that allows them to face ongoing technological and organizational challenges (Lawson and Lorenz, 1999). The case of Spanish STP initiatives, the focus of this paper, represents an evolving amalgam of these various approaches and rationales, realized through a combination of public and private efforts.

2.2. Empirical studies of STP

Several studies measure the impact of location in a STP on firms’ results or characteristics, such as growth, profitability, survival, innovative output and cooperative behaviour; for a sample of park companies and a control sample of off-park companies. Table 1 shows that the evidence from these studies is mixed. Common to all the studies is their small sample size, which ranges from 22 to 183 on-park firms, and 30 to 190 off-park firms. Also, most use a single methodology and do not control for endogeneity problems arising from location in a park (the decision to locate the company in an STP could be related to unobservable factors).[f] Finally, these studies are based on individual initiatives and do not refer to the same survey, so they use different indicators, sampling methods and methodologies.

[f] Only Siegel et al. (2003a), Fukugawa (2006) and Yang et al. (2009) try to take account of endogeneity.

Table 1: Studies measuring the effects of STP on firms

Study	Country (period)	Sample: on-park firms	Sample: off-park firms	Method	Main Result Variables	Results (effect of park location on firms)
Monck et al. (1988)	UK (1986)	183 F	101 F	Matching	growth (employment), links with HEI, patents, new products	no significant effects
Westhead (1997)	UK (1986-1992)	47 F	48 F	Matching	scientists and engineers, R&D expenditure, radical new research, patents, copyrights, new products	no significant effects
Löfsten and Lindelöf (2001)	Sweden (1994-1996)	163 NTBFs	100 NTBFs	Ordinary Least Squares	growth (employment-sales), profitability	effect (+) on growth. No significant effect on profitability
Löfsten and Lindelöf (2002, 2003); Lindelöf and Löfsten (2003, 2004); Dettwiler et al. (2006)	Sweden (1996-1998)	134 NTBFs	139 NTBFs	Matching Factor Analysis	growth (employment-sales), links with HEIs, profitability, product innovation, patents, motivations of location, strategies, Facilities Management (proximity -university, customers, competitors-infrastructure, cost of facilities)	effect (+) on growth, links with HEIs, proximity to universities, product innovation. No significant effect on other aspects.
Colombo and Delmastro (2002)	Italy (1999)	45 NTBFs	45 NTBFs	Tobit Matching	growth (employment), research personnel, use of TICs, external R&D, links with HEI, public financing, patents	effect (+) on growth, inputs innovation. No significant effect on patents
Siegel et al. (2003a)	UK (1992)	89 F	88 F	Negative Binomial, Two-Step Negative Binomial, Stochastic frontier	new products, patents, copyrights	effect (+) on new products and patents.
Ferguson and Olofsson (2004)	Sweden (1991-2000)	30 NTBF	36 NTBF	Matching	survival, growth (employment-sales)	effect (+) on survival. No significant effect on growth
Fukugawa (2006)	Japan (2001-2003) panel data	74 NTBF	138 NTBFs	bi probit	links with HEI	effect (+) on joint research with HEIs
Malairaja and Zawdie (2008)	Malaysia	22 HT-SME	30 HT-SME	Matching	links with HEI	no significant effects
Squicciarini (2008)	Finland (1970-2002) panel data	48 F	72 F	Before and after (duration model). Cox proportional hazard model	patents	effect (+) on patents
Yang et al. (2009)	Taiwan (1998-2003) panel data	57 NTBF	190 NTBF	Sample selection model (Heckman)	R&D Productivity	effect (+) on productivity
Key: F (firms); NTBF (new technology-based firms); HT-SME (high tech - small and medium-size enterprises); HEI (Higher education institutions)						

3. METHODOLOGY

We rely on statistical and econometric methods to analyse the causal effects of programmes or policies,[g] (so-called "treatment effects"), drawing on the *Rubin Causal Model* (Wooldridge, 2002) and the *Neyman-Rubin Counterfactual framework* (Guo and Fraser, 2010). For each unit i, for i = 1,…, n, we use an indicator W_i to indicate whether or not unit i participated in the treatment, with $W_i = 1$ if it did, and $W_i = 0$ otherwise. Each unit has two potential outcomes, one with treatment $Y_i(1)\ (if\ W_i = 1)$ and one without treatment $Y_i(0)\ (if\ W_i = 0)$, although only one of the two outcomes is observed. This implies that:

$$Y_i = Y_i(0)\,(1 - W_i) + Y_i(1)\,W_i$$

The construction of the counterfactuals is key to these evaluation methods (Blundell and Costa-Dias, 2002). Counterfactuals can be estimated in several ways, which depend on different assumptions about how treatment has been assigned. We distinguish between three types of assumptions: i) that treatment is assigned randomly (section 3.1.); ii) that treatment depends on the observed variables (section 3.2.) (in which cases independence is assumed between assignation of treatment and potential outcome); and iii) that treatment to an extent depend on potential outcomes (section 3.3).

In this work we focus on estimation of the Average Treatment Effect (ATE), understood as the expected effect of treatment on an individual drawn randomly from the population (Wooldridge, 2002). The ATE is estimated as the expected difference between outcomes with and without treatment:

$$ATE \equiv E\,[Y(1) - Y(0)]$$

To estimate outcomes, we analyse the existence and level of product innovation, with the treatment being location in an STP. Therefore, the ATE is the average expected difference between the potential probabilities and levels of product innovation of companies if they were located in an STP compared to if they were located off-park.[h] We estimate ATE based on equations I-IV (sections 3.2 and 3.3).

[g] For a revision of the literature, see Imbens and Wooldridge (2009) or Guo and Fraser (2010).

[h] Note that a distinction can be made between homogeneous and heterogeneous treatment effects. If treatment is assumed to be homogeneous the effect will be the same for all individuals. If heterogeneity is allowed the effect may vary with the characteristics of individuals. In this paper, we focus mainly on homogeneous effects. However, in equations (I) and (II) (see below) we relax this assumption; the ATE with heterogeneous effects are presented in Annex 1.

3.1. Methods assuming random treatment assignment

If treatment assignment is assumed to be random (completely independent of potential outcomes), $W_i \parallel Y_i(0), Y_i(1)$, ATE can be estimated by analysing differences in product averages for two groups of firms: the one inside and the one outside a park.

3.2. Methods assuming treatment assigned on the basis of observed variables

Treated and non-treated individuals are usually different which means there is selection bias (Imbens and Wooldridge, 2009). It is logical that this will be the case for firms in an STP owing to the fact there are usually some rules for entry. One assumption might be that of *Conditional Independence* (Rosenbaum and Rubin, 1983), meaning that, conditional to observed explanative variables (X), there are no unobservable factors simultaneously affecting treatment assignment and potential results.

$$W_i \parallel (Y_i(0), Y_i(1)) \mid X_i$$

In this case, ATE can be estimated by regression analysis using a sufficiently broad set of relevant covariates and assuming linearity of conditional expectations on potential outcomes, given the covariates (Imbens and Wooldridge, 2009). We employ two regression analyses: one with controls and one with propensity score.

3.2.1. Regression with controls

The regression with controls is represented in Equation I:

$$Y = \lambda + \alpha(SSTP) + \sum_{j=1}^{m} \beta_j X_j + u \quad \text{(I)}$$

where Y is an indicator of companies' product innovation, $SSTP$ indicates location in an STP, X are covariates suggested by the previous literature (see Table 2), and $\hat{\alpha}$ is the ATE.

3.2.2. Regression with Propensity Score

Propensity score is increasingly being used to evaluate treatment effects (Guo and Fraser, 2010), since it avoids the problems caused by huge differences in the means of the covariates by reducing the effect of multiple control variables to one dimension: the probability of treatment, $p(X)$, given the covariates X:

$$p(X) \equiv P(SSTP = 1 \mid X)$$

In the regression with propensity score (Wooldridge, 2002), this probability replaces the covariates, assuming that Y is linear in $p(X)$, leading to equation II:

$$Y = \lambda + \alpha(SSTP) + \pi[\hat{p}(X)] + u \quad \text{(II)}$$

where $\hat{\alpha}$ is the ATE.

3.3. Methods assuming treatment assigned on the basis of non-observed variables

The evaluation literature highlights the importance of endogeneity. The assumption of *Conditional Independence* must be abandoned and the potential existence of omitted or unobserved variables, which simultaneously influence treatment assignment and potential outcomes, needs to be taken into account. For example, a firm's decision to locate in an STP could be driven by unobservable factors, such as expectations about the benefits of such a location. This means that the estimated coefficients from the above methods will be inconsistent and biased (Wooldridge, 2003). We deal with the endogeneity problem applying two different methods: Control Function (CF) and Instrumental Variables (IV).

3.3.1. The CF approach

The CF approach treats endogeneity as an omitted variable problem and relies on the identification condition that the error term of the outcome equation must be uncorrelated with the observable factors in the treatment assigned.

This implies the following equation (a) to be added to equation (I):

$$SSTP^* = \gamma_0 + \sum_{j=1}^{m} \gamma_{1j} X_j + \gamma_2 Z - v, \qquad Var(v) = 1 \quad \text{(a)}$$

This equation considers that STP location is the outcome of a latent variable $SSTP^*$, which depends on the covariates of equation (I) and on Z, which acts as an exclusion restriction.

Location in or outside an STP is observed according to the following rule:

$$\begin{aligned} SSTP &= 1 \;\; if \;\; SSTP^* > 0 \\ SSTP &= 0 \;\; if \;\; SSTP^* \leq 0 \end{aligned}$$

where u (error term of equation I) and v (error term of equation a) follow a bivariate normal distribution with a mean of 0 and a covariance matrix: $\begin{bmatrix} \sigma & \rho \\ \rho & 1 \end{bmatrix}$.

This model can be estimated in two stages. In the first step we estimate equation (a) on the basis of a probit model, from which we obtain $\hat{\gamma}_0 + \sum_{j=1}^{m} \hat{\gamma}_{1j} X_j + \hat{\gamma}_2 Z$, hereafter $\gamma'_n X_n$.

For the second step, the model needs to be rewritten in the form of a switching model as proposed by Maddala (1983: 120 -121), thus expectations for Y, conditional on belonging or not to an STP are:

$$E(Y \mid SSTP=1) = \lambda + \alpha + \sum_{j=1}^{m} \beta_j X_j + \rho\sigma \frac{\phi \ (\gamma'_n X_n)}{\Phi \ (\gamma'_n X_n)} \qquad \text{(III.a)}$$

$$E(Y \mid SSTP=0) = \lambda + \sum_{j=1}^{m} \beta_j X_j + \rho\sigma * (-1) * \frac{\phi \ (\gamma'_n X_n)}{1-\Phi \ (\gamma'_n X_n)} \qquad \text{(III.b)}$$

where ϕ is the normal density function (evaluated using the term in parentheses which corresponds to the estimation obtained from the probit model) and Φ is the normal distribution function. In each case, the term that follows $\rho\sigma$ and multiplies it, is the so-called hazard; it acts as a control function to eliminate inconsistency in the standard regression, absorbing the correlation between treatment and the error term in the structural equation.

The second step then consists of estimating equations III.a and III.b simultaneously, employing the entire sample and restricting the coefficients of the covariates to being the same for both subsamples. That is, Y is regressed on the constant, $SSTP$, X and the hazard.

ATE is calculated on the basis of the difference between equations III.a and III.b:

ATE = $E(Y \mid SSTP=1) - E(Y \mid SSTP=0) = \hat{\alpha} + \hat{\rho}\sigma \left[\frac{\phi \ (\gamma'_n X_n)}{\Phi \ (\gamma'_n X_n) * (1-\Phi(\gamma'_n X_n))} \right]$ (III)

3.3.2. IV approach

The IV method deals directly with selection in the unobservables. It requires the existence of at least one regressor or instrument (Z) exclusive to the decision rule, thus fulfilling two restrictions: the exclusion restriction, meaning that potential outcomes do not vary from Z and the inclusion restriction, meaning that the instrument explains part of the variation in the treatment. Under the assumption of homogeneous effects, the IV estimator identifies the treatment effect with endogeneity.[i]

In this work we use IV with *propensity score*, which is more efficient than standard IV (Wooldridge, 2002: 623). It is assumed that the inclusion restriction of Z has a specific functional form for the propensity score[j]:

$$p_2 \ (SSTP=1 \mid X, Z) \neq p_2 \ (SSTP=1 \mid X) \ \ and \ \ p_2 \ (SSTP=1 \mid X, Z) = p_2 (X, Z; Y)$$

where $P_2(X, Z; Y)$ is the propensity score and can be estimated via a probit model.

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[i] However, in models assuming heterogeneous treatment effect, that is where the treatment effect varies across the individuals, the IV estimator only identifies ATE under strong assumptions, most of which are unlikely to hold in practice, which cautions against its use (Blundell and Costa-Dias 2002). Accordingly, in Annex 1 shows the estimations with heterogeneous effects only for Equations I and II.

[j] Assumes homoscedasticity as well as linearity of u in X.

We employ *propensity score* later as an instrument in a two-stage estimation analogous to the standard IV method. The first stage corresponds to the following estimation:

$$SSTP = \gamma_0 + \sum_{j=1}^{m} y_{1j} X_j + y_2 \hat{p}_2(X, Z) + v$$

The second stage estimates a structural equation, but using the treatment estimated in the previous step:

$$Y = \lambda + \alpha(\widehat{SSTP}) + \sum_{j=1}^{m} \beta_j X_j + u \qquad \text{(IV)}$$

where $\hat{\alpha}$ is the ATE.

4. DATA AND ESTIMATION METHODS

4.1. Database and variables employed

The study in this paper uses data from the Spanish Technological Innovation in Companies Survey 2007, undertaken by INE. This survey is modelled on the CIS, and is conducted annually. In 2007, the survey included a question about location of a company in a STP.

The sample population is 39,722 companies, representative of the size, sector and regional location of the population of Spanish companies.[k]

4.1.1. Dependent variables

The principal dependent variable is product innovation by companies, and is defined based on the responses to the question in the survey on percentage of company turnover from product innovations that are new to the market. The dependent variable (*newmar*) is measured as per thousand of total turnover (in 2007) from product innovations (introduced in the period 2005-2007) new to the market in which the company operates.

This indicator has been widely used since the introduction of CIS surveys because it has fewer limitations than many other indicators, such as *R&D*, which is actually an input (Love and Roper, 1999; Negassi, 2004), *patents*, which are a measure of invention but not of innovation, may not result in commercialization or economic advantage and are very unequally used across sectors (Griliches, 1990; Love and Roper, 1999; Faems et al., 2005), and *number of innovations* which does not reflect economic success (Negassi, 2004). The indicator we have chosen is applicable to all sectors, permits

[k] The specific characteristics of this sample are available on the INE webpage: http://www.ine.es/ioe/ioeFicha.jsp?cod=30061

differentiation among types of innovations and is also a continuous variable, which is an advantage for the econometric analysis (Kleinknecht et al., 2002; Negassi, 2004).[l]

In order to normalize our indicator to avoid possible problems related to residuals, we apply a logarithmic transformation (*tlnewmar*). We use a similar transformation to that employed by Faems et al. (2005) and Laursen and Salter (2006) in the case of similar indicators, and equals log(1+*newmar*).

We perform two types of estimations. First, we analyse this variable using the whole sample (aggregated estimation). Because many firms do not have sales from products new to the market we need to define a second dependent variable (V) which takes the value 1 if the firms has achieved a product new to the market and zero otherwise. 5,063 (12.7%) companies are product innovators (thus $V=1$).

As we explain (see section 4.2.2), in the second analysis (disaggregated or two part estimation), we use the whole sample to analyse V and then analyse *tlnewmar* using the subsample of product innovators ($V=1$).

4.1.2. Treatment variable

Based on a question about whether the company is located in an Spanish STP, we constructed a dichotomous variable (*SSTP*) that takes the value 1 if the company is located in one of the STP belonging to the Association of Science and Technology Parks of Spain (APTE) and 0 otherwise; this will be the treatment variable. There are 653 companies (1.64% of the sample) located in a Spanish STP.

4.1.3. Instrumental variable

Section 3.3.2, which deals with the IV method, refers to the need to have an instrumental variable for the treatment, which needs to comply with two restrictions: that of exclusion (not affecting the potential outcome) and that of inclusion (explaining the treatment). The variable we selected is the number of companies located in a STP as a percentage of total companies in the region in which the company is located (Z). This variable is calculated on the basis of information from the APTE on the number of firms in each park, and data from the Central Companies Directory (DIRCE) produced for the regional business census. We consider that this variable complies with both restrictions. Several studies agree that location in a particular region is not *per se* a significant explanatory factor for a firm's innovative outcome[m] when other factors are taken into account. Thus, company location in a region with a larger or smaller proportion of companies in a science park should not affect the firm's innovation outcomes,

[l] Its limitations include that larger firms will show very high turnovers based on previously consolidated products, resulting in a lower indicator despite high monetary income from new products; it is also very sensitive to product life cycle and, in the case of products new to the market, the market in which the company operates is used as the reference, but may not be the same for two competing companies, e.g. if one exports and the other does not (Kleinknecht et al., 2002; Frenz and Ietto-Gillies, 2009).

[m] E.g., Johansson and Hans (2008) find that the propensity to be innovative differs among regions, but that among innovative firms the intensity of innovation is not influenced by location. Sternberg and Arndt (2001) in a study of SME find that firm-specific determinants of innovation are more important than either region-specific or external factors.

and we would expect the exclusion restriction to be fulfilled. On the other hand, this variable can be interpreted as the supply or availability of “space” in the STP of a region and, consequently, will have a positive effect on the propensity of a company in that region to locate in a park. Thus, we also expect the inclusion restriction to be fulfilled.

We tested the strength of the instrument (enforcement of restriction of inclusion) based on the condition that the instrument (Z) and the endogenous regressor $(SSTP)$ are strongly correlated. This test is the first-stage F-statistic, developed by Staiger and Stock (1997) and described by Bascle (2008: 295-296), who consider this test to be both robust and conservative for proving the strength of an instrument. Intuitively, this test can be interpreted as a sophisticated F-statistic to test the hypothesis that the coefficient of the instrument is equal to zero in the structural equation. Using two stage OLS, this instrument is considered to be strong if the value obtained (when there is only one endogenous regressor) is higher than 9.08. Results confirm that Z is strong (F = 157.85).

One of the disadvantages of this instrument is its small variability: it shows only 19 values (one for each of the 19 Spanish regions). Because of this, we decided to use the IV method with propensity score (rather than standard IV). This means that the final instrument is propensity score, which increases the variability.[n]

We use this variable as the instrument (equations IV) and as the exclusion restriction in the estimation with control function (equation III).

4.1.4. Covariates

The choice of covariates is very important for the good working of the methods described in sections 3.2 and 3.3. We draw on the literature that uses CIS surveys to explain sales from new products (see Annex Table A3). There are two main groups of explanatory factors: the general characteristics of firms, and aspects related to innovative activity.

Among the general characteristics of firms some previous studies include indicators for size, foreign market presence, belonging to a group and firm sector. We control for all these characteristics and include three dummies to indicate if the firm is new or has merged or downsized in the previous three years. Table 2 presents detailed definitions of the covariates.

Among the aspects related to innovation activity, previous studies focus on innovative effort, cooperation and exploitation of different types of external sources. We control for all these characteristics and for the perception of various obstacles to the innovation process.

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[n] We conducted estimations using other IV related to region: regional distribution of physical space (in sq. m.) dedicated to parks. The results are very similar to those obtained using Z and, therefore, are not included here; they are available upon request from the authors.

Table 2: Definition of covariates

General Company Characteristics	
Company size	Total turnover in 2005 (in logarithmic transformation = natural logarithm of (1+indicator))
Exporting behaviour	Share of export per total turnover, in 2005
Group	Dummy variable being 1 if the company belonging to a group
Newly established	Dummy variable being 1 if the company was established during 2005-2007
Merged	Dummy variable being 1 if turnover increased by 10% or more due to merger with another company during 2005-2007
Downsized	Dummy variable being 1 if turnover decreased by 10% or more owing to sale or closure of part of the company during 2005-2007
Technological level of sectors of activity	7 dummy variables: high-tech manufacturing, medium-high-tech manufacturing, medium-low-tech manufacturing, low-tech manufacturing, knowledge intensity service, no-knowledge intensity service, other sectors[a].
Companies` Innovation Activity	
Innovation effort	Expenditure on innovation activities in 2007 ('000 euros per employee)
Cost obstacles	Average measure of importance of the following factors as a barrier to innovation during 2005-2007: lack of internal funds, lack of sources of finance, the high costs of innovating, market dominated by established enterprises[b]
Information obstacles	Average importance of the following factors as barriers to innovation during 2005-2007: lack of qualified personnel, lack of information on technology, lack of information on the markets, difficulty to find cooperation partners[b]
Cooperation	Dummy variable being 1 if the company cooperated on innovation with other companies or institutions during 2005-2007.
Market information sources for innovation	Average measure of importance of the following external knowledge sources for innovation during 2005-2007: clients, competitors, consultants, commercial laboratories/R&D institutes[c]
Institutional information sources for innovation	Average measure of importance of the following external knowledge sources for innovation during 2005-2007: universities or other HEI, government research organizations, technology centres[c]
Other information sources for innovation	Average measure of importance of the following external knowledge sources for innovation during 2005-2007: conferences, fairs, exhibitions, scientific publications, professional associations[c]

[a] Classification of manufacturing and services (OECD, 2005). Other sectors: agriculture; extractive activities; production and distribution of electricity, gas and water; construction
[b] Importance is on the scale of 1(crucial) to 4 (unimportant).The indicator is equal to [n / ∑ factors importance]
[c] Measured similarly to the case of the barrier to innovation.

4.2 Estimation Method

4.2.1. Aggregated estimations

Because the dependent variable studied here is censored owing to the concentration of observations at its minimum/maximum values,[o] the most appropriate way to perform the estimations is via double-censored Tobit models.[p]

[o] There are two censor points in the dependent variable *tlnewmar*: $c_1 = 0$ in 34,659 observations (87.25% of cases) and $c_2 = 6.90$ in 604 observations (1.5%).

If we take equation (I) in Section 3.2.1, the existence of a latent variable $Y*$ can be assumed:

$$Y* = \lambda + \alpha(SSTP) + \sum_{j=1}^{m} \beta_j X_j + u$$

Y takes the following values:

$$\begin{aligned} Y &= Y* \quad if \quad Y* > c_1 \\ Y &= c_1 \quad if \quad Y* \leq c_1 \end{aligned}$$

$$\begin{aligned} Y &= Y* \quad if \quad Y* < c_2 \\ Y &= c_2 \quad if \quad Y* \geq c_2 \end{aligned}$$

Although the equations in Section 3.3 - treatment assignment on the basis of non-observed variables (equations III and IV) - are designed in principle for continuous (but not censored) dependent variables, and thus for an estimation using OLS, an extension can be made of the procedures appropriate to censored variables (by adapting the estimation form). Wooldridge (2002) states that although many of the assumptions supporting ATE estimation methods, based on treatment assignment on the principle of non-observed variables, cannot be strictly true for binary dependent variables and Tobit-like responses, this ATE estimation method may produce reasonable estimations in these cases. Angrist (2000) highlights that the problem of estimating the causal effect for *limited-dependent variables (LDV)* is essentially the same as for continuous variables. Angrist and Pishke (2008) recommend using OLS for estimation treatment effects on these kinds of variables, since empirically marginal effects from non linear models are very close to OLS coefficients. Accordingly, all the equations in the methodological section (Equations I-IV) are estimated by Tobit models and by OLS to enable comparison (column 1 in Table 4)

4.2.2. Disaggregated (two-part) estimations

A limitation of the standard Tobit model is that the same mechanism determines the choice between $Y = 0$ and $Y > 0$ and the quantity of Y, given that $Y > 0$. The Tobit model assumes that the relative effect of the explanatory variables upon the probability of event $P(Y > 0 \mid SSTP, X)$ and upon the conditional expectation of $Y : E(Y \mid SSTP, X,\ Y > 0)$ is identical, and thus this model analyses the two aspects integrally. To overcome this limitation we use a two-part model (Wooldridge, 2002; Cameron and Trivedi, 2005)

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[p] Depending on the specific configuration of the innovation surveys, some authors, using the same dependent variable, consider there to be a problem of missing data since the only firms able to report sales due to new products are those that have obtained new products, and therefore choose generalized Tobit or selection models (see e.g., Mohnen and Dagenais (2000); Mairesse and Mohnen (2001, 2005); Raymond et al. (2006); Eom and Lee (2010)). In the Spanish case we consider that there is no such selection problem since all the surveyed firms are required to respond to the questions related to innovation inputs and innovation outputs. Thus, firms with no new products have zero sales from new products. We follow Negassi (2004) and Laursen and Salter (2006) and the recommendation in Mairesse and Mohnen (2010).

Since it is feasible to assume that there may be different effect of the independent variables and, specifically, the treatment variable, on the probability of companies being innovators and on the expectation of product innovations (conditional on their being innovative companies), we choose to estimate a two-part model.

The two-part model requires the estimation of two equations:

(a) the probability of the event $P(V) = P\,(Y > 0 \mid SSTP, X)$

$$P\,(V) = P\,(Y > 0 \mid SSTP, X) = \lambda + \alpha(SSTP) + \sum_{j=1}^{m} \beta_j X_j + u$$

where the event $V = Y > 0$ is the company's introduction of a new to the market product innovation, in the period 2005-2007, that is, of being an innovative company. To determine this probability we estimate a probit model using the same explanatory variables as in the standard Tobit model and utilizing all the observations. The OLS estimation is presented in column 2 in Table 4.

(b) the conditional expectation of $Y : E\,(Y \mid SSTP, X,\ Y > 0)$)

$$E\,(Y \mid SSTP, X,\ Y > 0) = \lambda + \alpha(SSTP) + \sum_{j=1}^{m} \beta_j X_j + u$$

This equation is similar to Equation (I), but utilizes only those observations that comply with the event $V = Y > 0$, that is, it takes account only of the subsample of innovative companies. Restricting our estimation to this subsample permits us to include in the estimation variables to control for the way in which the company conducts the process of innovation (covariates R). It also allows us to exclude some of the control variables, contained in X, considered relevant to the probability of the event occurring, but not to the conditional expectation of a new product. In this case, the variables referring to the obstacles to innovation are removed in the second part of the estimation.[q]

Thus, to estimate part (b) in the two-part model, we apply a Tobit model but this time with right censoring;[r] this again assumes the existence of a latent variable y^b, equal to:

$$Y^* = \lambda + \alpha(SSTP) + \sum_{j=1}^{m-2} \beta_{1j} x_j + \sum_{j=1}^{m} \beta_{2j} R_j + u$$

and Y takes the following values:

$$Y = Y^* \quad if \quad Y^* < c_2$$
$$Y = c_2 \quad if \quad Y^* \geq c_2$$

[q] We ran the regressions including these variables but the results did not change, which is logical since their coefficient are very close to zero. Note that the different roles of the obstacles for innovators and non innovators is a highly controversial issue (D´Este et al, 2008).
[r] Because we consider only innovative companies, the possibility of observing zeros in this indicator is eliminated.

The results of this specification are given in column 3 in Table 4.

5. RESULTS

5.1. Results assuming random treatment assignment

Table 3 shows that the average value of *tlnewmar* for firms located in an STP is significantly higher than for companies located outside a park. This result is observable for the total sample and the subsample of product innovators, although in the latter case the magnitude of the differences is smaller.

Table 3: Difference in the means of the dependents variables for companies in and outside an STP

	Total Sample (39.722 Observations)			**Sub sample Innovative product companies** (5.063 Observations)		
	Companies in an STP	Companies outside an STP	Difference	Companies in an STP	Companies outside an STP	Difference
tlnewmar	2.34	0.61	1.73	5.67	5.02	0.65
V	0.41	0.12	0.29	------	-------	--------
# of companies	653	39,069		270	4,793	
All differences are significant at 1%						

5.2. Results assuming treatment assignment on the basis of observed variables

Table 4 presents the estimations of the ATE using regression analyses (Equations I and II) and the Tobit/probit and OLS estimation methods. In what follows we refer mainly to the results of the Tobit and probit estimations since the OLS are quite similar in terms of the direction and p-values of the coefficients. Table 5 presents the marginal effects for both the average firm (the mean values of all the covariates) and the median firm (the median values of the covariates). The results are discussed in section 5.4.

The results of the two regression analyses, which assume treatment assigned on the basis of the observed variables, are similar.

5.2.1 Regression with controls (Equation I)

According to the regression with controls, location in a Spanish STP has a positive and significant effect on a firm's innovation output. This effect is very strong for the total sample. For the two part disaggregated model, the effect of location upon the firm's propensity to be a product innovator is also positive and strongly significant. It is estimated that location in an Spanish STP increases the probability of being an innovator by 12 percentage points for the average firm, and 18 percentage points for the median firm, holding all else constant (OLS estimates a 16 percentage point increase). Once a company has decided to be a product innovator the effect of park location on innovative outcome remains positive and significant, although the degree of significance is lower. This result is in line with the previous descriptive analysis. The proportion of sales due to new products shows an increase of 32 per cent for both the average and the median firm.

5.2.2 Regression with propensity score (Equation II)

The results are similar for the regression with *propensity score* (Tables 4 and 5). Again, location in a science park has a positive and significant effect on firms' innovation and the effect is more significant in the aggregated and the first part of the disaggregated models compared to the second part of the latter model. The marginal effects are also very similar. The likelihood of being a innovator increases by 14 and 13 percentage points respectively for the average and the median firm located in a park and percentage of sales increases by 31 per cent in both cases.

5.3. Results assuming treatment assignment on the basis of non-observed variables

5.3.1 Endogeneity tests

Before commenting on the results obtained assuming treatment assigned on the basis of non-observed variables, it should be underlined that we tested for treatment endogeneity.

First, we follow the procedure described in Wooldridge (2003: 483), which is in two stages.

a) First, v is estimated using the residuals from the reduced form of the STP equation:

$$SSTP = \pi_1 + \pi_2 Z + \sum_{j=2}^{m} \pi_{3j} X_j + v$$

b) Then $\hat{v}$ is included in the structural equation (I.1), which is estimated using OLS:

$$Y = \lambda + \alpha(SSTP) + \sum_{j=1}^{m} \beta_j X_j + \phi\,\hat{v} + u$$

If $\phi \neq 0$, STP is endogenous. This is the result for the aggregated model and for the first part of the disaggregated model (Table 6). However, if only innovators are accounted for, endogeneity is rejected. This result is logical since these firms are already selected: all have achieved new to the market products.

We also performed a Hausman test to compare the coefficients of the OLS and the two stage OLS (2SLS) regressions. The null hypothesis is that there are no systematic differences among the coefficients from these regressions. Endogeneity is present in both models for the whole sample but not if only product innovators are considered (Table 6).

Thus, we only account for endogeneity in the regressions for the whole sample (the aggregated model and the first part of the disaggregated model). This section presents the results obtained if we do not assume conditional independence in the estimations. The results of the ATE and marginal effects estimates do not change significantly compared to the results in the previous section.

5.3.2 CF Approach (Equation III)

In the case of CF, the results are similar to those obtained in the regression analysis. Location in an Spanish STP is clearly positive for the whole sample. It is estimated that location in a science park increases the probability of being a innovator by 15 percentage points for the average firm and by 19 percentage points for the median firm, holding all else constant (again, OLS shows an increase of 16 percentage points).

5.3.3 IV with *propensity score (Equation IV)*

Results using IV with *propensity score* show a positive effect of location in a park for the aggregated model. The first part of the two part model shows a positive coefficient both for the probit model and OLS.[s] The marginal effects are quite similar to those calculated using other methodologies. The increase in the likelihood of being an innovator is 10 percentage points for the average firm and 17 percentage points for the median firm.

Accordingly, accounting for the endogeneity of location in a park does not produce large variations in the results, even in the aggregated and the first part of the disaggregated models where exogeneity is rejected. This suggests that the set of covariates used is good enough to account for the most relevant factors.

Table 4: ATE estimation of location in an STP, on product innovation

	Aggregated Model	Disaggregated two-part Model	
	$E(Y)$	$P(V)$	$E(Y \mid Y>0)$
Dependent variable	*tlnewmar*	V	*tlnewmar*
Tobit / Probit estimations	Tobit	Probit	Tobit
Regression with controls (Eq. I)	4.50[a] (0.425)	0.52[a] (0.057)	0.36[a] (0.105)
Regression with propensity score (Eq. II)	4.77[a] (0.461)	0.52[a] (0.060)	0.35[a] (0.107)
Control function (Eq. III)	6.30[a] (0.006)	0.74[a] (0.000)	------ ------
IV with propensity score (Eq. IV)	9.75[a] (3.133)	0.58 (0.538)	------ ------
OLS estimations	OLS	OLS	OLS
Regression with controls (Eq. I)	1.05[a] (0.067)	0.16[a] (0.012)	0.33[a] (0.093)
Regression with propensity score (Eq. II)	1.04[a] (0.069)	0.17[a] (0.013)	0.32[a] (0.095)
Control function (Eq. III)	0.87[a] (0.000)	0.16[a] (0,000)	------ ------
IV with propensity score (Eq. IV)	3.68[a] (0.477)	0.55[a] (0.089)	------ ------
# of observations	39722	39722	5063
Standard errors in parentheses, [a]Coefficients significant at 1%. All controls from Table 2 are included in the regressions			

[s] When instrumental variables probit estimators of this type are used, coefficients are consistent but standard errors are not (Adkins, 2010). This is the reason why coefficient in the first part of the two part model is not found to be significant. When OLS is used this problem is overcome and the coefficient becomes significant again.

Table 5: ATE Marginal Effects

	Disaggregated two-part Model			
	$P(V)$		$E(Y \mid Y>0)$	
Dependent variable	V		*tlnewmar*	
Tobit/probit estimations	Probit		Tobit[a]	
	Mean	Median	Mean	Median
Regression with controls (Eq. I)	0.122	0.184	32.19	32.18
Regression with propensity score (Eq. II)	0.138	0.128	31.01	31.59
Control function (Eq. III)	0.154	0.197	------	------
IV with propensity score (Eq. IV)	0.102	0.177	------	------

[a] Marginal effects in %

Table 6: Tests of treatment endogeneity

	Aggregated Model		Disaggregated two-part Model			
	$E(Y)$		$P(V)$		$E(Y \mid Y>0)$	
Dependent Variable	*tlnewmar*		V		*tlnewmar*	
I. Test of treatment endogeneity (Wooldridge, 2003)[a]						
Coefficient of $\hat{v}$	-10.32[a]	(1.071)	-1.91[a]	(0.191)	0.89	(1.174)
II. Test de Hausman (endogeneity) [b]						
Chi2(1)	92.51[a]	(0.00)	81.74[a]	(0.00)	0.59	(0.44)
# of observations	39722		39722		5063	

[a] Standard errors in parentheses, [b] Prob>chi2 in parentheses

5.4. Results for covariates

Table 7 presents the results for the covariates in Equation I, III and IV. The signs of the coefficients are in line with those found in the literature (see Annex Table A3).

First, among the general characteristics, size is found to have a positive and significant effect in the double censored Tobit and the probit models. However, its influence is negative and significant in the second part of the two part model.[t] These results are useful to reconcile the lack of consensus among previous studies on the influence of size on the percentage of sales from new products (Annex Table A3). The group coefficient is positive in the double censored Tobit and the probit models, but not in the second part of the two part model, while the effect of exports is clearly positive in all the models. Both sets of results are in line with the literature as is sectoral influence where firms in high-tech sectors are shown to perform better in the double censored Tobit and the probit models than firms in any other sector. However, there are no significant difference across sectors in the second part of the model. Finally, the effect of being a new firm is clearly positive in all models while merged and downsized firms show respectively more and fewer sales from new products only in the double censored Tobit and the probit models.

[t] Although the coefficients point to a non-linear influence, the negative effect of size holds only for firms with less than €1,040 worth of sales in the double censored Tobit and less than €895 worth of sales in the probit model. Conversely, in the second part of the two part model the effect is negative after €503 worth of sales.

Table 7: Results of the control variables in the estimations (Tobit / probit estimations)

		Aggregated Model			Disaggregated two-part Model			
		$E\,(Y)$			$P(V)$			$E\,(Y \mid Y > 0)$
	Dependent variable	*tlnewmar*			V			*tlnewmar*
	Equation	**I**	**III**	**IV**	**I**	**III**	**IV**	**I**
General Company Characteristics	size	-0.43[a] (0.05)	-0.41[a] (0.05)	-0.43[a] (0.05)	-0.05[a] (0.00)	-0.05[a] (0.00)	-0.05[a] (0.00)	0.09[a] (0.01)
	size ^2	0.03[a] (0.00)	0.03[a] (0.00)	0.03[a] (0.00)	0.00[a] (0.00)	0.00[a] (0.00)	0.00[a] (0.00)	-0.00[a] (0.00)
	behaviour of exports	6.68[a] (0.50)	6.59[a] (0.49)	6.60[a] (0.50)	0.83[a] (0.06)	0.83[a] (0.06)	0.83[a] (0.06)	0.31[a] (0.11)
	group	1.27[a] (0.17)	1.27[a] (0.17)	1.23[a] (0.18)	0.14[a] (0.02)	0.14[a] (0.02)	0.14[a] (0.02)	-0.01 (0.05)
	newly established	1.62[a] (0.38)	1.59[a] (0.39)	1.41[a] (0.41)	0.13[a] (0.04)	0.12[a] (0.04)	0.13[a] (0.05)	0.50[a] (0.11)
	merged	1.30[a] (0.48)	1.35[a] (0.47)	1.32[a] (0.48)	0.17[a] (0.05)	0.18[a] (0.05)	0.17[a] (0.05)	-0.00 (0.13)
	downsized	-1.14[c] (0.60)	-1.09[c] (0.59)	-1.14[c] (0.60)	-0.12[c] (0.07)	-0.12[c] (0.07)	-0.12[c] (0.07)	0.11 (0.19)
	low tech manufacturing	-5.50[a] (0.37)	-5.72[a] (0.38)	-5.28[a] (0.40)	-0.69[a] (0.04)	-0.72[a] (0.04)	-0.68[a] (0.05)	-0.00 (0.10)
	medium-low tech manufacturing	-4.77[a] (0.38)	-4.98[a] (0.39)	-4.53[a] (0.41)	-0.60[a] (0.04)	-0.64[a] (0.04)	-0.60[a] (0.05)	0.05 (0.10)
	medium-high tech manufacturing	-1.76[a] (0.37)	-2.03[a] (0.38)	-1.55[a] (0.39)	-0.23[a] (0.04)	-0.26[a] (0.04)	-0.23[a] (0.05)	-0.08 (0.09)
	knowledge intensity service	-0.45 (0.36)	-0.53 (0.36)	-0.53 (0.37)	-0.09[b] (0.04)	-0.10[b] (0.04)	-0.09[b] (0.04)	0.09 (0.09)
	no-knowledge intensity service	-8.43[a] (0.37)	-8.61[a] (0.38)	-8.22[a] (0.40)	-1.02[a] (0.04)	-1.04[a] (0.04)	-1.01[a] (0.05)	-0.11 (0.10)
	other sectors	-8.43[a] (0.43)	-8.59[a] (0.44)	-8.20[a] (0.45)	-1.01[a] (0.05)	-1.04[a] (0.05)	-1.01[a] (0.04)	-0.02 (0.13)
Companies´ Innovative Activity	Innovation effort	0.01[a] (0.00)	0.05[a] (0.00)	0.01[a] (0.00)	0.003[a] (0.00)	0.008[a] (0.00)	0.003[a] (0.00)	0.002[a] (0.00)
	cost obstacles	8.52[a] (0.42)	8.36[a] (0.42)	8.44[a] (0.43)	1.01[a] (0.04)	1.01[a] (0.05)	1.01[a] (0.04)	-----
	information obstacles	-1.08[c] (0.55)	-0.93[c] (0.55)	-1.08[c] (0.55)	-0.14[b] (0.06)	-0.13[b] (0.06)	-0.14[b] (0.06)	-----
	cooperation	-----	-----	-----	-----	-----	-----	-0.14[a] (0.04)
	market information sources	-----	-----	-----	-----	-----	-----	0.23 (0.18)
	institutional information sources	-----	-----	-----	-----	-----	-----	0.46[a] (0.17)
	other information sources	-----	-----	-----	-----	-----	-----	0.16 (0.16)
# observations		39722			39722			5063

The reference technological sectoral level is high-tech manufacturing.
In Equation II, the effects of the control variables are contained in the *propensity score*.
Standard errors in parentheses.
[a]Coefficients significant at 1%, [b]Coefficients significant at 5%, [c]Coefficients significant at 10%.

Second, for companies´ innovation activity, innovative effort is the most important characteristic. It is positive in all models. This is the least controversial of the results in the literature. The effect of cost obstacles is positive in the double censored Tobit and the probit models while the reverse is true for information obstacles. That is, those firms that lack the financial resources to carry out their innovation process are more innovative than well financially endowed firms, and firms that lack information and knowledge are less innovative than firms with greater information and knowledge resources. Finally, cooperation and sources of information are included only in the second part of the two-part model, because they are only observed for innovators. The effect of cooperation is significantly negative, while most previous studies and especially the most recent, find it to be not significant. We find also that information from institutional sources has a significantly positive effect while information from markets and other sources has no effect.

6. CONCLUDING REMARKS

Our objective was to evaluate the impact of Spanish Science and Technology Parks (STP) on firms' product innovation. Governments are increasingly interested and active in creating conditions that are conducive to innovation through the establishment of localized mechanisms of knowledge development and transmission including STP.

This study provides new empirical evidence by using a very large sample of firms from the Spanish Innovation Survey provided by INE. This sample allows us to analyse the ATE of STP location under different assumptions, and to use a set of already proven variables as covariates. The large size of our sample and the large number of STP considered, make our results highly representative, especially since the characteristics of parks differ and STP are established based on different approaches and rationales.

The set of methods employed show that location in an Spanish STP positively affects product innovation by firms. If we disaggregate this effect, we find that the results are robust to different assumptions about how treatment is assigned, in terms of both the likelihood of product innovation, and the level of product innovation for the subsample of product innovators. We show that the effect of location in a park increases the probability of being an innovator by between 10 and 20 percentage points, and increases sales due to new product for innovators by around 32 per cent. Unfortunately, these figures are not comparable with the findings from previous studies as the measures used are different.

A limitation of this study is that we assume that the effect of location in a science park is homogeneous for all firms. In order to test the influence of this assumption we relaxed it for equations I and II. The results are fairly stable (see Annex I), which suggests that this assumption is not influencing the conclusions derived from the analysis. However, we believe that the possibility that firms with particular characteristics would benefit more from a park location is an important issue that deserves further research. We provide empirical evidence that Spanish STP help firms to achieve product innovations, but we do not analyse why and how this happens. We also focus on ATE, but do not analyse other indicators of impact, such as average effect on the treated firms. All these aspects should be investigated in future research.

The main result that STP have a positive impact on the product innovation efforts of Spanish firms adds to the (mixed) evidence in the literature on the effect of science parks on firm performance. It should be noted, however, that the literature shows that STP play different roles in some countries, such as Italy, Greece and Spain, by providing a more advanced environment for firms than obtains in off-park locations. However, in the case of well developed countries, such as Sweden, the USA and the UK, the off-park environment is advanced so an STP location has less of an impact.

Acknowledgments

The authors want to thank the Spanish Institute of Statistics for allowing access to the data and Annamaría Conti and Alberto López for comments on previous versions of the paper. A version of this paper was presented at DRUID 2010 and Encuentro de Economía Aplicada 2010. The usual disclaimers apply. We acknowledge funding from project "Evaluación del Impacto de los Parques Científicos y Tecnológicos Españoles", funded by Spanish Department of Science and Innovation.

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Annex 1: ATE under heterogeneous effects

The heterogeneous version of the model takes account of the possibility that belonging to an STP affects companies differently, depending on their characteristics, as defined by the covariates. This annex presents the methodological approach for the estimation of ATE assuming heterogeneous effects and results. It takes into account the two equations in the methods assuming treatment assigned on the basis of non-observed variables.

1. Regression with controls and heterogeneous effects

If treatment effects are heterogeneous for the different values of X, that is, they interact with X,[u] equation (I) is modified as follows (Wooldridge, 2002):

$$Y = \lambda + \alpha(SSTP) + \sum_{j=1}^{m} \beta_j X_j + \sum_{j=1}^{m} \delta_j [(SSTP)(X_j - \overline{X_j})] + u \quad \text{(I.2)}$$

where the estimated coefficient of SSTP is the ATE.

2. Regression with *Propensity Score* and heterogeneous effects

If the assumption of homogeneity of treatment effects is relaxed the modified version of equation (II) is:

$$Y = \lambda + \alpha(SSTP) + \pi [\hat{p}(X)] + \delta [(SSTP)(\hat{p} - \bar{\hat{p}})] + u \quad \text{(II.2)}$$

where the estimated coefficient of SSTP is the ATE.

The results of equations (I.2) and (II.2) (Table A.1) shows that location in an STP has a positive and significant effect on firm innovation. Note, though, that in equation (I.2), in the second part of the disaggregated model, the effect is not significant although the value of the coefficient is similar to the homogeneous case.

It is estimated that location in a park increases the probability of being an innovator by between 16 and 27 percentage points for the average firm and by about 25 percentage points for the median firm (Table A.2), which effects are slightly higher than in the homogeneous case. The percentage of sales due to new products increases by between 28 and 31 per cent both for the average and the median firm, this increment is only slightly lower than the homogeneous effect.

[u] Effects of treatment can be heterogeneous depending upon the control variables or upon the unobservable variables, included in the error (*u*) Lee (2005).

Table A1: ATE estimation of location in a STP upon product innovation. Heterogeneous effects

	Aggregate Model		Disaggregate two-part Model			
	$E\,(Y)$		$P(V)$		$E\,(Y,\ Y>0)$	
Dependent variable	*tlnewmar*		V		*tlnewmar*	
Tobit / Probit estimations	Tobit		Probit		Tobit	
Regression with controls (Eq. I.2)	5.49[a]	(0.892)	0.67[a]	(0.114)	0.36	(0.287)
Regression with propensity score (Eq.II.2)	7.77[a]	(0.578)	0.91[a]	(0.064)	0.32[b]	(0.147)
OLS estimations	OLS		OLS		OLS	
Regression with controls (Eq. I.2)	0.89[a]	(0.112)	0.17[a]	(0.021)	0.39	(0.259)
Regression with propensity score (Eq.II.2)	1.43[a]	(0.086)	0.25[a]	(0.016)	0.33[a]	(0.130)
# of observations	39722		39722		5063	
Standard errors in parentheses, [a]Coefficients significant at 1%,[b]Coefficients significant at 5%						

Table A2: ATE Marginal Effects. Heterogeneous effects

	Disaggregate two-part Model			
	$P(V)$		$E\,(Y\,|\,Y>0)$	
Dependent variable	V		*tlnewmar*[a]	
Tobit / Probit estimations	Probit		Tobit	
	Mean	Median	Mean	Median
Regression with controls (Eq. I.2)	0.167	0.245	31.32	31.37
Regression with propensity score (Eq. II.2)	0.276	0.260	27.65	28.16
[a] Marginal effects in %				

To conclude, the results of the estimation of ATE of location in an STP with heterogeneous effects do not vary significantly in relation to the results obtained assuming homogeneous effects.

Annex 2: Studies using indicators related to innovative product sales

Table A3·: Studies using indicators related to innovative product sales

Study	Data[a]	Dependent Variable[b]	Independent Variables (more frequent)[c]						
			General Company Characteristics				Companies` Innovative Activity		
			Size	Foreign Market	Group	Sector	Innovative Effort	R & D Cooperation	External Knowledge Sources
Brouwer, Kleinknecht (1996 a,b)	CIS 1 Netherlands		LE	X / V	d sub	2 d	rdp / E	d	d
		% n_firm	(-)	(+)	ns		(+)	ns	ns
		% n_market	(-)	ns	(+)		ns	ns	ns
Crepón et al. (1998)	France 2001		E			18 d	L S RDi /E		3 d
		L% n_i_general	ns				(+)		(+)
Mohnen, Dagenais (2000)			E (n)		d	10 d	Gi / V	d	
	CIS 1 Denmark	LT$_1$% n_i_general	ns		(+)		ns	ns	
	Ireland		ns		ns		(+)	ns	
Mairesse, Mohnen (2001)	CIS 2 France		L E		d	4 d / 6 d	Gi / V	d	d
		LT$_1$%n_i_general[d]	(+) (+)		ns (+)		(+) ns	ns ns	ns
Klomp, Van Leeuwen (2001)	CIS 2 Netherlands		L V			9 d	G / V	d	2 d
		% n_i_general	ns				(+)	(+)	(+)
Janz, Peters (2002)	Germany 1999		LE, LE^2	X / V		12 d	G / V		5 d
		% n_i_general	(+), (-)	ns			(+)		ns
		% n_market	ns, ns	(+)			(+)		ns
Miotti, Sachwald (2003)	CIS 2 France		L E		d	4 d	d RDi	d	d
		% n_i_general	(+)		ns		(+)	(+)	ns
Negassi (2004)	CIS 1 and 2 France		L V				S RDi	€	
		VA n_i_general	(+)				(+)	(+)	
Caloghirou et al. (2004)	Gr, It, De, Uk, Fr, Ger, Ne 2000		L E			4 d	rdp / E	d	5 d
		% n_i_general	ns				(+)	ns	(-) (+) ns ns ns
Faems et al. (2005)	CIS 2 Belgium		L E		d su	9 d	rdp / E	# partners	
		LT$_2$% n_i_general	ns		(-)		(+)	(+)	
		LT$_2$% n_general	(-)		ns		(+)	---	
		LT$_2$% improved	ns		(-)		ns	---	
Mairesse, Mohnen (2005)	CIS 3 France		L E	d	d	4 d, 6 d	L Gi / E		
		LT$_1$ %n_i_general	ns , ns				(+), (+)		
		LT$_1$ % n_market[d]	ns , ns				(+), (+)		
Mohnen et al. (2006)	CIS 1 Be, De, Ger, Ir, It, Ne, No		LE		d	4 d, 7 d	Gie / V	d	d
		LT$_1$% n_general[d]	(+), (+)		(+), (+)		(+), (+)	(+), ns	(+)
Laursen, Salter (2006)	UK 2001		L E	c		13 d	Gi / V	d	use, use^2, imp, imp^2
		LT$_2$ % n_general	(+)	(+)			(+)	(+)	(+), (-), (+), (-)
		LT$_2$ % n_market	ns	(+)			(+)	(+)	(+), (-), (+), (-)
		LT$_2$ % improved	(+)	(+)			(+)	(+)	(+), (-), ns, ns
Raymond et al. (2006)	Netherlands		L E			4d, 4d, 0	L Gie / V	d	d
	CIS 2	L% n_i_general[e]	(-) (-) (-)				(+) (+) ns	(+) ns (+)	ns ns ns
	CIS 2,5		(-) (-) ns				(+) (+) ns	(+) (+) ns	ns ns ns
	CIS 3		(-) (-) (-)				(+) ns ns	(+) (+) (+)	ns (+) ns

Table A3: Studies using indicators related to innovative product sales

Study	Data[a]	Dependent Variable[b]	Independent Variables (more frequent)[c]						
			General Company Characteristics				Companies` Innovative Activity		
			Size	Foreign Market	Group	Sector	Innovative Effort	R & D Cooperation	External Knowledge Sources
Cassiman, Veugelers (2006)	CIS 1 Belgium		V	X / V			G / V		
		% n_i_general	(-)	(+)			(+)		
Falk (2007)	CIS 3 12 Countries		d V	d	d su	6 d	Gi / V		
		% n_general	(-)	(+)	(+)		(+)		
		% n_market	(-)	(+)	(+)		(+)		
Aschhoff, Schmidt (2008)	Germany 2004 and 2005		LE			11 d	G/E,G/E^2	d	
		% n_firm	(+)				(+), (-)	ns	
		% n_market	ns				ns, ns	ns	
Fosfuri, Tribó (2008)	CIS 3 Spain		L E	X / V			L Gi	d	L S pat
		% n_i_general	(-)	(+)			(+)	ns	(+)
Hussinger (2008)	CIS 1,2 and 3 Germany		L E			13 d	Gie / E		
		L % n_general	(+)				(+)		
Tsai (2009)	Taiwan 2002		E		d su	8 d	S Gif / E		Gtl
		P n_i_m_general	(+)		ns		(+)		(+)
		P n_i_general	ns		ns		(+)		ns
		P modified	(+)		(+)		(+)		(+)
Frenz, Ietto-Gillies (2009)	CIS 2 and 3 UK		LE	d	d su	13 d	LT Gi	d	
		L P n_i_general	ns	ns	ns		(+)	ns	

Signs in parentheses are effects statistically significant at least at 10%. ns = No significant

[a] CIS1 (1990-92); CIS2 (1994-96); CIS3 (1998-2000)

[b](%) Share of ___ in firm's total sales; (L) Logarithm; (LT_1%) Logarithmic Transformation = L [% / (100-%)]; (LT_2%) Logarithmic Transformation = L (1 + %); (VA) Absolute Value (P) Productivity (VA / employees); (modified) Marginally modified products; (improved) Significantly improved products; (n_firm) New products to firm; n_market) New products to firm's market; (n_general) New products, (n_i_general) New and significantly improved products; (n_i_m_general) New , significantly improved and marginally modified products.

[c] (L) Logarithm; (LT) Logarithmic Transformation = L (1 + X); (E) Total Employees; (V)Total Sales; (d) Dummy variable; (c) Categorical variable; (rdp) R&D employees; (S) Stock; (RDi) Internal R&D; (G) Expenditure on innovation activities; (Gi) internal R&D expenditure; (Gie) internal and external R&D expenditure; (Gif) Internal R&D and training expenditure; (X) Value of exports; (su) Subsidiary firm; (pat) Patents; (Git) Expenditure on technology licences

[d]Make two estimates: high-R&D sectors (4 sectors) and low-R&D sectors (6 sectors / 7 sectors)

[e] Make three estimates: high-tech sectors (4 sectors), low-tech sectors (4 sectors) and wood.