Public Policy, Innovation and Total Factor Productivity: an application to Taiwan's manufacturing industry (1997-2003)

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Abstract:

This paper examines the impact of being an innovator on firm productivity in Taiwan. Using a panel of 48794 firms observed over the 1997-2003 period, and distributed across 23 industries, we compute TFP by estimating Translog production functions with conventional K, L, E, M inputs. We evaluate the impact of being an innovator on TFP using propensity score matching. The rationale is that, over the period, innovating firms are likely to have benefited from one of many innovation policy measures known as IUS (until 1999) or "New IUS" (after 1999). The analysis was conducted separately for 1997-1999 and for 2000-2003. Our results show a significantly negative effect of being an innovator on TFP in every 2-digit industry and in both sub-periods. If TFP is defined as the part of productivity unexplained by conventional inputs, then this means that innovation activities explain a significant part of productivity at the firm level.

JEL classification: D24,L60, O33

Keywords: Newly industrialized countries; Total Factor Productivity; Propensity Score Matching; Firm-level panel data; Manufacturing industry.

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Since the beginning of the 1990s, Taiwan has been increasingly challenged by international competition, especially from other Asian newly-industrialized and developing countries. A steep rise in labour costs put a heavy pressure on the economy, while the adoption of a (managed) floating exchange rate made exported products less competitive on the international market. As a result, Taiwan had to speed up its industrial upgrading process. Industrial policies encouraging traditional firms to upgrade their technological level have been implemented. Other policies, promoting Research and Development (R&D) activities and technology upgrading, have been designed to accelerate the development of high-technology firms (expected to play a leading role in the new Taiwanese economy).

The present research uses a sample of 48794 manufacturing firms, distributed across twenty-three 2-digit industries, to investigate the impact of Taiwan's innovation policy on sales in the late 1990s and early 2000s. The paper is organized as follows: Section 1 defines the aims and scopes of the study, and reviews the evolution of Taiwan's science and innovation policies since the 1990s. Section 2 describes the data. The analytical framework is presented in Section 3, and the estimations results are given in Section 4. A final section summarizes our conclusions.

1. Aims and scope of the study

The issue of how innovation affects the growth of productivity is an important one in economics, and becomes critical when considering industrializing economies. Early studies focusing on the rapidly-growing Japanese economy of the 1960s and 1970s (Caves and Uekusa, 1976; Odagiri, 1983) highlighted a diversified impact of innovation inputs on firms' productivity or sales growth. For instance, Odagiri (1983) found that R&D expenditures affect positively the current and future growth of sales in industries with a high research intensity, whereas they tend to affect negatively future sales growth in industries with low research intensity. Moreover, patents purchases have a negative impact on future sales growth.

More recent studies, such as that conducted by Basant and Fikkert (1996) on a panel of Indian firms observed from 1974 to 1981, still point out mixed results. On the one hand, Basant and Fikkert (1996) find that firms purchasing foreign technology can expect high and statistically significant private returns. On the other hand, the authors find private returns to firms' in-house R&D rather low and often insignificant.

Therefore, the global impact of innovation activities (such as R&D and technology purchase) on productivity in a developing economy is still debatable. For instance, if technology purchases yield better returns than R&D in developing economics, then one can expect a positive impact of innovation expenditures on productivity if and only if those expenditures are mostly dedicated to technology upgrading rather than to in-house R&D. Moreover, given what was said above, the impact of innovation expenditures on productivity may vary hugely across industries: it may be positive in some high-tech industries, and negative in others.

The objective of the present paper is to examine this question in the case of Taiwan, using a recent panel of firms. We will attempt to estimate the effects of innovation expenditures on the economic performance of Taiwanese firms, measured by Total Factor Productivity (TFP). In the specific case of Taiwan, increase in innovation expenditures at the firm-level can be directly linked to a specific set of public policy measures, actively promoting industrial and technological upgrading.

The history of innovation in Taiwan is not a long one: although the 1980s saw the emergence of Taiwan's high-tech industries (esp. electronic components), innovation activity (as measured by innovation expenditures) at the firm level really started in the 1990s. This evolution seems to be directly linked to Taiwan's industrial and innovation policy, the cornerstone of which have been, since January 1st, 1991, the Statute for Upgrading Industry (Hou and Gee, 1993; Luo, 2001), hereafter SUI[3].

The SUI consists in a number of incentive measures aimed at encouraging investment and technology transfers in emerging and/or strategic industries (i.e. industries that are expected to benefit economic development in a substantial way). A first set of measures involve taxation policy and direct public spending:

- tax incentives to develop investment in R&D and process innovation.
- preferential loans (arranged through the Executive Yuan Development Funds, in conjunction with banks) for the upgrading of small and medium enterprises(SMEs) and the promotion of industrial R&D.
- specialized programs providing support for technical upgrading, new product development, and R&D.
- public institutes and centers providing extensive support to the private sector in developing new technology.

A second set of measures is oriented towards education policy, with the objective of upgrading the stock of human capital. These measures include:

- on-the-job training provided by various academic organizations, in order to give workers the skills to succeed in emerging industrial sectors[4].
- doubling to six years the maximum period of stay in Taiwan by skilled mainland Chinese technicians.
- increasing the employment of mainland technical personnel at innovative R&D centers.
- enabling wider civilian employment among armed forces R&D personnel.

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[3] See http://www.moeaidb.gov.tw/portal/english/about3.jsp and http://www.environet.org.tw for more details about the IUS.

[4] According to http://www.environet.org.tw, 120000 professional engineers underwent such training between 1991 and 1995.

- establishing institutes to foster talent in high-tech industries (e.g., semiconductors).

A third and final set of measures was specifically implemented to encourage technology transfer and to accelerate the flow and commercialization of innovative knowledge. They include:

- the establishment of science-based industrial parks (a.k.a. "science parks") to facilitate the development of high-tech industries.
- the establishment of a platform for technical exchange between domestic and foreign businesses and academic organizations (a.k.a. Taiwan Technology Marketplace or TWTM).

The SUI was first designed to be effective until 31st December, 1999. After 2000, due to the continued need for economic structural transformation and the promotion of international competitiveness, a New SUI was implemented, with an effective period of 10 years, from January 1st, 2000, to 31st December, 2009. The objective of this paper is to estimate the economic impact of the policy change caused by the transition from the SUI to the New SUI. Failing to observe the implementation of the actual policy measures, we use innovation activities (i.e. R&D and/or technology purchases) at the firm level as proxies, and examine their impact on firms' Total Factor Productivity (TFP).

2. Data: The MOEA Panel

To achieve our objective, we use census data gathered by the Statistic Bureau of Taiwan's Ministry of Economic Affairs (MOEA). The Statistical Bureau of the MOEA conducts a yearly census survey, and collects data on every plant in operation that holds a registered certificate in the manufacturing sector. This data covers all manufacturing industries in the Taiwanese economy. In Taiwan, more than 90% (see Table 1) of all manufacturing firms are single-plant producers, which suggests that distinguishing between plant and firm is not as relevant as in other countries. We will therefore refer to the MOEA data as 'firm-level data' hereafter.

For this research, we use a panel of 48794 firms covering the 1997-2003 period, with year 2001 missing (no survey was conducted on that specific year). Those firms are distributed across twenty-three 2-digit industries (see definitions and breakdown by industry in Table 1). The data provides information on firms' sales, total value of fixed assets in operation at the end of the year, total sum of gross wages, number of employees, energy expenditures, total expenditures on raw materials. Additional information includes firm age and an indicator of whether or not a plant is part of a multi-plant structure.

Finally, the MOEA data allows us to define innovating firms on the basis of their innovation expenditures. More precisely, two binary variables indicate whether a firm reported R&D expenditures and/or technology purchases in any given year. We define a firm that has reported at least one of these two types of expenditures as an “innovating firm”. Since the number of firms relying only on the purchase of technology to innovate is extremely small, we define a global indicator of “innovation expenditures”, which is equal to 1 if a firm has recorded R&D expenditures or technology purchases, and to 0 otherwise. In spite of this rather broad definition, the proportion of innovating firms remains fairly small in every 2-digit industry, except in high-tech industries such as (26) ‘Audio & video products’ and (27) ‘Electronic parts & components’ (see Table 1).

INSERT TABLE 1 ABOUT HERE

3. Theoretical framework and empirical analysis

To estimate the impact of being an innovating firm on TFP, we adopt a two-step empirical strategy: in a first step, we estimate a Translog production for each of the 2-digit analysis observed in the MOEA panel. We use the parameter estimates to compute TFP for each observation in a given industry. In a second step, we estimate the impact of being an innovator on TFP using non-parametric propensity score matching techniques.

An important aspect of our empirical analysis is that innovators (as defined in Section 2) are contrasted with the control group of non-innovators both before and after a policy change: the transition from the SUI to the New SUI that occurred at the end of 1999. We therefore conduct our propensity score matching analysis first on the 1997-1999 period, and then on the 2000-2003 period; when then compare the results (differences between innovators and non-innovators) across the two periods, in what can be seen as a differences-in-differences type of approach.

3.1. Computation of TFP

We obtain our measure of the TFP of Taiwanese firms by estimating a production function, linking sales (our measure of firm output Q) to inputs X. For firm i operating at time t in a given 2-digit industry, we write:

$$(1) \qquad Q_{it} = F(X_{1it}, X_{2it}, X_{3it}, X_{4it})$$

where X_1, X_2, X_3 and X_4, denote, respectively, capital, labor, energy and materials (a.k.a. K, L, E, M inputs in the literature). To conduct our empirical analysis, we need to specify a functional form for F, which we want to keep as flexible as possible. We therefore assume a Translog specification, which is usually considered as a reasonable second-order approximation of an arbitrary production function (e.g., Berndt & Christensen, 1973; Chan & Mountain, 1983; Beason & Weinstein, 1996). We may then rewrite (1) as:

$$\text{(2)} \qquad \ln Q = \beta_0 + \Sigma_j\, \beta_j.\ln X_{jit} + \frac{1}{2}[\Sigma_j\, \Sigma_k \delta_{jk.}(\ln X_{jit})(\ln X_{kit})]$$

$$+ \beta_T.T + u_i + \varepsilon_{it}$$

where T is a vector of year dummy variables (time-fixed effect), u_i a firm-specific effect (specified as a fixed-effect), and ε_{it} a transitional error term.

INSERT TABLE 2 ABOUT HERE

We conducted some preliminary tests for the autocorrelation of residuals in every 2-digit industry, using the methodology proposed by Drukker (2003). As can be seen in Table 2, those tests revealed the presence of autocorrelation of order 1 in every industry except (22) 'Non-Metallic Mineral Products' and (30) 'Precision instruments". To circumvent this problem, we assume ε_{it}, in Equation (2), to be autoregressive of order 1 (AR1):

$$\text{(3)} \qquad \varepsilon_{it} = (1 - d/2).\varepsilon_{i,t\text{-}1} + \nu_{it}$$

where d is the Durbin-Watson statistics and where ν_{it} is supposed to be i.i.d.

We estimate this model using fixed-effect regression with AR(1) errors[5], and use the parameter estimates to compute TFP (these parameter estimates will be presented in Section 4). The first step is to compute technical change TC for each firm i at time t:

$$\text{(4)} \quad TC_{it} = \partial ln\ Q_{it} / \partial T = \sum_{t=2}^{4} \hat{\beta}_T$$

Under the usual symmetry assumption (i.e., $\delta_{jk} = \delta_{kj},\ \forall\ j,\ k$), we can also compute input shares, for k = 1, 2, 3, 4:

$$\text{(5)} \quad S_{kit} = \partial ln\ Q_{it} / \partial ln\ X_{kit} = \hat{\beta}_k + \Sigma_j\ \hat{\delta}_{kj}.\ln X_{jit} \quad \text{with} \quad j = 1, 2, 3, 4.$$

Returns to scale are then defined as the sum of input shares over k = 1, 2, 3, 4:

$$\text{(6)} \quad \mathrm{RTS}_{it} = \Sigma_k\, S_{kit}$$

Finally, we can compute TFP for firm i at time t as (Kumbhakar and Lovell, 2000):

$$\text{(7)} \quad TFP_{it} = TC_{it} + (RTS_{it} - 1).\ \Sigma_k\, (S_{kit}.X_{kit})/RTS_{it}$$

[5] While estimating Equation (2), we performed a test of the Translog versus Cobb-Douglas specifications, by testing the restriction H_0: "$\delta_{jk} = 0,\ \forall\ j, k$". The null hypothesis was rejected at the 1% level in every 2-digit industry, indicating that the Translog should be the preferred specification.

3.2. Non-parametric estimation of the impact of being an innovator on TFP

Several stylized facts suggest that considering the fact of being an innovator as a treatment could be a reasonable assumption. First, until very recently, Taiwanese firms were very reluctant to innovate – hence the SUI. Second, due to the large set of measures encompassed in the SUI, any firm who engaged in innovative activities (either R&D or technology purchases) in the 1990s and afterwards is likely to have benefited from one of these measures. Moreover, it seems that the first SUI did not spur the innovation effort of Taiwanese firms enough (at least in the eyes of Taiwan's authorities), so that it had to be re-conducted in a new form after 1999. This suggests that a simple analysis over the 1997-2003 period may not be sufficient: it seems necessary to conduct a "differences-in-differences" type of analysis, i.e. to contrast the differences in TFP across innovators and non-innovators both before and after December 31st, 1999.

For each sub-period (pre- and post-December 31st, 1999), we estimate the effect of being an innovator (considered as a treatment) on TFP using propensity score matching (Rosenbaum & Rubin, 1983, 1985). The underlying principle of the method consists in matching together treatment and comparison units (i.e. innovator and non-innovators) that are similar in terms of their observable characteristics. Although widely used, this method rests on the (strong) Conditional Independence Assumption (CIA): in other words, it is assumed that selection on unobserved variables do not affect outcomes in the absence of the treatment.

Under the CIA, estimators relying on matching techniques can yield unbiased estimates of the Average effect of the Treatment on the Treated (ATT), such as, in the present study, the effect of being an innovator on firms' productivity. Propensity score matching is generally considered as a valid approach if a very rich dataset is used to build the propensity score. In other words, one wants to control for all variables (including retrospective variables) that can affect participation or non-participation in the treatment. However, as the method grew increasingly popular, researchers have become more concerned with the sensitivity of the ATT estimates to unobserved heterogeneity (e.g., Caliendo & Kopeinig, 2005; Aakvik, 2001; Aakvik *et al.,* 2005).

To build our propensity score, we estimate the probability of being an innovator (as defined in Section 2), using a binary Logit model on the pooled data[6]:

$$(8) \quad \Pr(y_{it} = 1) = \frac{\exp(\gamma . Z_{it})}{1 + \exp(\gamma . Z_{it})}$$

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[6] We also estimated a Logit model for panel data, but this did not affect significantly our results, and in particular did not seem to affect the ATT estimates.

where y_{it} is a binary variable equal to 1 if a firm is an innovator or to 0 otherwise, Z_{it} a vector of explanatory variables, and γ a vector of parameters to be estimated. Our explanatory variables include: firm size (measured by the number of employees) and its square, firm age, a measure of market concentration (the Herfindhal index, or H index, computed at the 2-digit industry level), a dummy variable indicating whether a plant is part of a multi-plant firm, a dummy variable indicating whether a firm exports technology, and a year fixed effect (i.e. year dummies, with 1997 being the reference).

The Logit model described in Equation (8) is estimated in each 2-digit industry, first over the whole period (1997-2003), and then for each sub-period (1997-1999 and 2000-2003), following a differences-in-differences type of approach. We therefore have two different versions of our propensity score: a less flexible one, p, computed over the whole period, and a more flexible one (actually two scores, p_a and p_p), computed for each sub-period (before and after the New IUS). We implement propensity score matching on these two versions of the propensity score. For each version, we estimate the ATT using two different non-parametric matching algorithms: nearest neighbour and kernel (Heckman *et al.*, 1997, 1998).

After computing the ATT, we conduct a number of tests: first, we verify that the enforcement of the *common support* (achieved by dropping treated observations whose propensity score is higher than the maximum or less than the minimum of the controls) does not lead to the loss of an excessive fraction of the treated. Second, we check whether the balancing property holds for our various estimations of the ATT, i.e. whether individuals with the same propensity score have the same distribution of observables. To do so, we simply observe whether matching reduced the average (absolute) standardized bias[7].

Last but not least, we examine the sensitivity of the ATT estimates to unobserved heterogeneity: we apply the so-called "Rosenbaum bounds" approach, adopting the methodology developed by Becker & Caliendo (2007). Let us assume that the propensity score $p(z_{it})$ of a given firm i at time t is influenced by both its observed characteristics z_{it} and by some unobserved time-invariant variable v_i. Since we used a Logit model to compute the propensity score, we can write, for firm i:

$$(9) \quad p(z_{it}) = \Lambda(\gamma.z_{it} + \lambda.v_i) = \frac{\exp(\gamma.z_{it} + \lambda.v_i)}{1+\exp(\gamma.z_{it} + \lambda.v_i)}$$

[7] The average (absolute) standardized bias is formally defined as the (absolute value of the) difference of the sample means in the treated and control groups, as a percentage of the square root of the average of the sample variances in the treated and controls groups (Rosenbaum & Rubin, 1985).

where γ and λ are parameters measuring the respective effects of observed and unobserved variables on the propensity score. For two matched firms *i* and *j*, the odds that individuals are part of the treated are given by:

$$(10)\quad \frac{p(z_{it})}{1-p(z_{it})} \quad \text{and} \quad \frac{p(z_{jt})}{1-p(z_{jt})} \quad \text{respectively,}$$

and the odds ratio is given by:

$$(11)\quad \frac{\dfrac{p(z_{it})}{1-p(z_{it})}}{\dfrac{p(z_{jt})}{1-p(z_{jt})}} = \frac{p(z_{it})[1-p(z_{jt})]}{p(z_{jt})[1-p(z_{it})]} = \exp[\gamma(v_i - v_j)].$$

Since, by definition, $\gamma.z_{it} = \gamma.z_{jt}$ for matched firms *i* and *j*, the equality in Equation (11) follows immediately when replacing $p(z_{it})$ and $p(z_{jt})$ by the Logistic function given in Equation (9).

Rosenbaum (2002) has shown that Equation (11) implies that the odds-ratio that two matched individuals both belong to the treatment group is bounded:

$$(12)\quad \frac{1}{\exp\gamma} \le \frac{p(z_{it})[1-p(z_{jt})]}{p(z_{jt})[1-p(z_{it})]} \le \exp\gamma$$

Both matched individuals will have the same probability of being treated only if $\gamma = 0$, i.e. if $\exp\gamma = 1$. The exponential of γ can therefore be used as a measure of the degree of departure from a study that is free of unobserved heterogeneity bias. For given values of γ such that $\exp\gamma > 1$, it is possible to test the assumption that the ATT is over- or under-estimated due to the presence of unobserved heterogeneity, using the non-parametric Mantel-Haenszel test-statistic (Aakvik, 2001; Rosenbaum, 2002). We implement this test using Becker & Caliendo (2007)'s method.

3.3. Lagged estimation of the ATT

Because R&D expenditures (and technology imports) are inputs in the so-called “knowledge production function”, their effect on firms' productivity is difficult to assess. In particular, one has to take into account that the innovation process is long and uncertain. It is therefore not uncommon, when measuring the impact of knowledge (as measured by R&D expenditures) on TFP, to used lagged values. Indeed, a three-years period (on average) is often considered as necessary to observe returns on R&D expenditures.

Since our dummy variable identifying innovators is based on the observations of knowledge inputs, we may face a similar problem here. To circumvent this problem, we implement our non-parametric estimation of the ATT with a lag. We compute the propensity score as in Section 3.2., using a Logit model over the

1997-1999 and 2000-2003 periods. We then estimate the ATT for 1999 using the propensity score computed in 1997, and the ATT for 2003 using the propensity score computed in 2000. As in section 3.2., we then examine the common support and check the balancing property.

4. Results

4.1. Estimation of TFP values

As explained in Section 3.1., we estimated a translog production function with K, L, E, M inputs in every 2-digit industry, and used the production function estimates to compute technical change TC, returns to scale RTS and TFP. The estimated values of TC, RTS and TFP for each industry are given in Table 3 (the detailed results of the estimation are available upon request from the authors).

INSERT TABLE 3 ABOUT HERE

A first look at Table 3 reveals that TC is at its highest in two industries: (17) 'Basic Chemical Matter Manufacturing' and (23) 'Basic Metal'. Unsurprisingly, those are traditional industries which have played an important role in Taiwan's economy (esp. chemical matter), and where technological upgrading has been important since the mid-1990s. TC is also quite important in high-tech industries such as (26) 'Audio & Video Products', (30) 'Precision Instruments' and (28) 'Electric Machinery and Parts', which makes sense.

Somewhat surprisingly, TC is high, but no so high, in industry (27) 'Electronic Parts and Components': this may be because the production of electronic components has become a stabilized trademark of Taiwan's economy. More surprising is the high value of TC in industry (12) 'Leather and Fur Products', where it could be expected to be as low as in other traditional industries such as (10) 'Textile Mills Products' or (13) 'Wood and Bamboo Products'. We have no clear explanation as to why TC is so high in industry (12); it may be that this industry has become dedicated to the production of luxury goods, and therefore has needed to upgrade its production processes.

A second important result summarized in Table 3 is that, unsurprisingly, TFP is generally high in industries where TC is high. In particular, we find high TFP values in upgrading traditional industries such as (17) and (23), as well as reasonably high values of TFP in high-tech industries (26), (28) and (30). If we define TFP as the part of productivity which is not explained by the conventional K, L, E and M inputs, then these results make sense: TFP should be high in traditional industries that are upgrading their technological level, and in high-tech industries. Again, as far as high-tech industries are concerned, (27) 'Electronic Parts and Components' appears to have a relatively low TFP. As before, we find a puzzling result in industry (12), where TFP is unexpectedly high.

Finally, we observe from Table 3 that, in every 2-digit industry, RTS are close to one, which is consistent with the classical idea of a constant returns-to-scale technology. In other words, assuming a production function with constant returns to scale in every industry would be, in the context of our data, a rather reasonable approximation.

4.2. Computation of the propensity score

As explained in Section 3.2., we used a Logit model on the pooled data in order to compute our propensity score. This model was estimated in every 2-digit industry, for the 1997-1999 period and for the 2000-2003 period. The results of these estimations are given in Tables 4.a and 4.b. For the sake of concision, we will not comment these tables in details, but we will focus on results that concern two specific determinants of the propensity to innovate: firm size (measured by the number of employees) and market concentration (measured by the Herfindahl index).

INSERT TABLE 4.a ABOUT HERE

INSERT TABLE 4.b ABOUT HERE

First of all, we observe that, in every industry, the probability of being an innovator (i.e. either to have R&D expenditures or to import technology) strongly depends on firm size. More precisely, a look at Tables 4.a and 4.b reveals that, in every 2-digit industry, this relationship can be characterized by an “inverted-U” curve: the probability to be an innovating firm increases with firm size up to a certain threshold, after which it decreases (the estimated coefficient are positive for firm size and negative for the square of firm size). This is consistent with results observed in the literature (see for instance Scherer, 1965, 1986a, 1986b), including results regarding Taiwan (Chang and Robin, 2006).

The effect of market concentration seems to be confined in a small number of industries, over either one or both of our observations periods. In most of these industries, we observe an inverted-U relationship between market concentration and the probability to be an innovating firm, which is again consistent with the literature. In industries (17) ‘Basic Chemical Matter Manufacturing’ and (26) ‘Audio & Video Products’, this relationship is U-shaped over the 1997-1999 period and disappears in the subsequent period (a rationale for this U-shaped relationship can be found in Scott, 1993, 2005).

4.3. Estimation of the effect of being an innovator on TFP

We now move to the core of our analysis, i.e. the estimation of the effect of being on innovator on TFP. As was said in Section 3, this effect is estimated using propensity score matching. Table 5 provides us with the ATT, estimated over each period using two different matching algorithms: nearest neighbour and kernel. Overall, we observe a negative ATT in every 2-digit industry; this negative effect is more significant when the ATT is estimated using kernel. The transition from the IUS to the new IUS does not seem to affect this result, as the ATT remain significant in almost all industries over both the 1997-1999 and 2000-2003 periods.

INSERT TABLE 5 ABOUT HERE

We propose the following interpretation for this result: if we define (somewhat conservatively) TFP as the part of productivity which is not explained by the conventional K, L, E, and M inputs, then it seems sensible that innovating firms have a lower TFP. This simply means that innovation activities (measured here by our proxy on the existence of some innovation inputs) explain a significant part of productivity at the firm level. Moreover, given that most innovating firms in Taiwan have received some kind of support from the IUS or New IUS, it is not unreasonable to think that these sets of policy measures have helped increase firms' productivity.

INSERT TABLE 6 ABOUT HERE

In order to check the robustness of our results, we first examined the common support and checked the balancing property. We found that, in every industry, there were 100% (close to 100%) of "treated" firms on support (i.e. matched to corresponding firms in the control group on the basis of their propensity score). In order to check the balancing property, we observed whether matching has reduced the average absolute standardized bias (as explained in Section 3.2). Table 6 shows that, for both nearest neighbour and kernel algorithms, the average absolute standardized bias has been dramatically reduced after matching.

INSERT TABLE 7 ABOUT HERE

Finally, we tested whether unobserved firm heterogeneity may affect our results, using the methodology described in Section 3.2. Table 7 shows the results of a Mantel-Haenszel test of the null hypotheses that the ATT is either over- or under-estimated in our analysis. The test was conducted using values of γ ranging from 1 to 2 in steps of 0.05. A quick glance at Table 7 shows that we cannot reject the null hypothesis of an overestimation, nor the null hypothesis of an underestimation. Our results should therefore be interpreted with caution.

As a further test of robustness, we also conducted (as explained in Section 3.3) a matching analysis on the lag of the propensity score. Instead of comparing TFP, in year t, of firms matched on their probability of being an innovator in year t (our contemporaneous benchmark analysis), we compared TFP, in year $t + n$, of firms matched on their probability of being an innovator in year t. More precisely, we compared TFP in 1999 on the basis of the propensity score observed in 1997, and TFP in 2003 on the basis of the propensity score observed in 2000. This was done in order to take into account the fact that the innovation process does not yield instant output, but occurs over a certain period of time.

INSERT TABLE 8 ABOUT HERE

The result of this “lagged” analysis are presented in Table 8, which gives, for each period, the ATT estimated by both nearest neighbour and kernel algorithms. Again, in both periods, we find a negative ATT in most 2-digit industries (the results obtained with the nearest neighbour algorithm tend to be less significant, overall, than those obtained with kernel). We interpret this result as before: if TFP measures the part of firm productivity which is not explained by the K, L, E, M inputs, then our findings suggest that innovation activities may explain a significant part of firms’ productivity.

As before, we examined the common support and checked the balancing property. Again, we did not observe any problem of common support, and found that, in every industry and in both periods, the average absolute standardized bias has been dramatically reduced after matching (as can be seen in Table 9). The only exception is industry (19) ‘Petroleum and Coal Products’, in which the average absolute standardized bias increases when the ATT is estimated with the nearest neighbour algorithm.

INSERT TABLE 9 ABOUT HERE

5. Conclusion

The objective of this paper was to examine the impact of being an innovator on productivity at the firm level in Taiwan. To do so, we used a panel of 48794 firms observed over the 1997-2003 period (with year 2001 missing), and distributed across twenty-three 2-digit industries. We computed TFP at the firm level by estimating a Translog production function with conventional K, L, E, M inputs in each 2-digit industry.

We then built a proxy variable indicating whether a firm was an innovator or not, and measured the impact of being an innovator on TFP using propensity score matching. The rationale for using propensity score matching was that, over the period, an innovating firm was likely to have benefited from one of the many innovation policy measures known as IUS – and thus could be considered as “treated”. The analysis was conducted separately for 1997-1999 and for 2000-2003, sub-periods which correspond to two different set of policy measures: the IUS and “New IUS” respectively.

Our results show a significantly negative effect of being an innovator on TFP in every 2-digit industry. This result is quite robust across both sub-periods, and does not depend on the algorithm used for matching. Moreover, this effect persists whether matching is performed on the propensity score (i.e. the probability to innovate) or on a lag of the propensity score. Robustness checks showed that our analysis does not suffer from a problem of common support, and that the balancing property is respected. However, we cannot reject the hypothesis that our ATT estimates may be biased by unobserved heterogeneity.

We interpret this result as follows: if TFP is defined as the part of productivity unexplained by the conventional K, L, E, M inputs, then it means that innovation activities explain a significant part of productivity at the firm level. Moreover, given that most innovating firms in Taiwan have received some kind of support from the IUS or New IUS, it is not unreasonable to think that both sets of policy measures may have helped increase firms' productivity.

References

Aakvik, A. (2001) "Building a matching estimator: the case of a Norwegian training program", *Oxford Bulletin of Economics and Statistics*, 63(1), pp. 115-143.

Aakvik, A., J.J. Heckman and E.J. Vytlacil (2005) "Estimating treatment effects for discrete outcomes when responses to treatment vary: an application to Norwegian vocational rehabilitation programs", *Journal of Econometrics*, 125, pp. 15-51

Basant R. and B. Fikkert, 1996, "the Effects of R&D, Foreign Technology Purchase, and domestic and International Spillovers on Productivity in Indian Firms," *The Review of Economics and Statistics*, pp.187-199.

Beason R. and D.E. Weinstein, (1996) "Growth, economies of scale, and targeting in Japan (1995-1990)", *Review of Economics and Statistics*, 78(2), pp. 286-295.

Becker S.O. and M. Caliendo, (2007) "Sensitivity analysis for average treatment effects", *The Stata Journal*, 7(1), pp. 71-83.

Berndt E. and L. Christensen, (1973) "The translog function and the substitution of equipment, structures, and labor in US manufacturing, 1929-1968", *Journal of Econometrics*, 1, pp. 81-114.

Caliendo M. and S. Kopeinig (2005) "Some Practical Guidance for the Implementation of Propensity Score Matching", *DIW Discussion Papers,* n° 485, DIW, Berlin.

Caves R.E. and M. Uekusa (1976), *Industrial Organization in Japan,* The Brooking Institution, Washington, D.C. pp.124-140.

Chan, M.W.L. and D.C. Mountain, (1983) "Economies of scale and the Törnqvist discrete measure of productivity growth", *Review of Economics and Statistics*, 70, pp. 663-667.

Drukker, D. M. (2003) "Testing for serial correlation in linear panel-data models", *Stata Journal*, 3, 168–177.

Heckman, J.J., H. Ichimura, and P. Todd (1997) "Matching as an econometric evaluation estimator: evidence from evaluating a job training programme", *Review of Economic Studies*, 64, pp. 605-654

Heckman, J.J., H. Ichimura, and P. Todd (1998), "Matching as an econometric evaluation estimator", *Review of Economic Studies*, 65, pp. 261-294.

Hou, C.M. and S. Gee (1993) "National systems supporting technical advance in industry: the case of Taiwan" in R. Nelson (Ed) *National Innovation Systems*, Oxford University Press.

Kumbhakar and Lovell (2000) *Stochastic Frontier Analysis*, Cambridge University Press.

Luo, Y-L. (2001), *National Innovation System of Taiwan*, STIC – National Science Council, Taiwan.

Odagiri, H., 1983, "R&D Expenditures, Royalty Payments, and Sales Growth in Japanese Manufacturing Corporations," *The Journal of Industrial Economics*, 32, September, pp.61-71.

Rosenbaum, P.R. and Rubin, D.B. (1983), "The central role of the propensity score in observational studies for causal effects", *Biometrika*, 70(1), 41-55.

Rosenbaum, P.R. and Rubin, D.B. (1985), "Constructing a control group using multivariate matched sampling methods that incorporate the propensity score", *The American Statistician*, 39(1), 33-38.

Rosenbaum, P.R. (2002) *Observational Studies* (2nd Edition), Springer.

Scherer, F.M. (1965) "Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions", *American Economic Review*, 55, pp. 1097-1125.

Scherer, F.M. (1986a) "Statistical Evidence on Antitrust Decree Effects", in F.M. Scherer (Ed.) *Innovation and Growth: Schumpeterian perspectives*, MIT Press, Cambridge, MA, pp. 207-221.

Scherer, F.M. (1986b) "Corporate Size, Diversification, and Innovative Activity", in F.M. Scherer (Ed.) *Innovation and Growth: Schumpeterian perspectives*, MIT Press, Cambridge, MA, pp. 222-238.

Scott, J.T. (1993) *Purposive Diversification and Economic Performance*, Cambridge University Press, Chapters 7, pp. 84-90, and 10, pp. 133-147.

Scott, J.T. (2005) "Corporate Social Responsibility and Environmental Research and Development", *Structural Change and Economic Dynamics*, 16, pp. 313-331.

Table 1: breakdown of the panel by 2-digit industry

2-digit industry		Breakdown by industry		single-plant	Innovating
		Frequency	%	firms (%)	firms (%)
8	Food Manufacturing	3164	6.5	88.7	8.2
10	Textile Mill Products	1945	4.0	86.9	9.4
11	Wearing Apparel & Accessories	1453	3.0	91.0	5.8
12	Leather & Fur Products	642	1.3	91.9	8.6
13	Wood & Bamboo Products	924	1.9	95.1	2.6
14	Furniture & Fixtures	977	2.0	91.8	5.4
15	Pulp, Paper & Paper Products	992	2.0	90.9	5.9
16	Printing Processing	1411	2.9	94.5	2.8
17	Basic Chemical Matter Manufacturing	712	1.5	76.5	25.3
18	Chemical Products	1410	2.9	87.6	22.3
19	Petroleum & Coal Products	117	0.2	81.1	15.1
20	Rubber Products Manufacturing	682	1.4	87.2	10.2
21	Plastic Products Manufacturing	4868	10.0	90.0	4.8
22	Non-Metallic Mineral Products	1644	3.4	83.8	8.6
23	Basic Metal Industries	1542	3.2	84.5	7.7
24	Fabricated Metal Products	6964	14.3	93.1	4.5
25	Machinery & Equipment	9710	19.9	93.2	4.9
26	Audio & video products	969	2.0	83.8	31.7
27	Electronic parts and components	1420	2.9	82.8	24.5
28	Electric machinery and parts	2206	4.5	88.7	13.3
29	Transportation Equipment	2367	4.9	88.0	11.4
30	Precision Instruments	723	1.5	88.7	15.1
31	Miscellaneous Industrial Products	1948	4.0	91.7	6.8
Total manufacturing		48790	100	90.1	8.4

Table 2: test of H_0: "no first-order autocorrelation of residuals" by 2-digit industry

Industry		Test statistic	p-value	Conclusion
8	Food Manufacturing	86.41	0.000	H_0 rejected at 1% level
10	Textile Mill Products	5.41	0.020	H_0 rejected at 5% level
11	Wearing Apparel & Accessories	19.39	0.000	H_0 rejected at 1% level
12	Leather & Fur Products	4.16	0.042	H_0 rejected at 5% level
13	Wood & Bamboo Products	7.19	0.008	H_0 rejected at 1% level
14	Furniture & Fixtures	10.68	0.001	H_0 rejected at 1% level
15	Pulp, Paper & Paper Products	10.71	0.001	H_0 rejected at 1% level
16	Printing Processing	16.11	0.000	H_0 rejected at 1% level
17	Basic Chemical Matter Manufacturing	13.28	0.000	H_0 rejected at 1% level
18	Chemical Products	16.96	0.000	H_0 rejected at 1% level
19	Petroleum & Coal Products	5.33	0.023	H_0 rejected at 5% level
20	Rubber Products Manufacturing	18.80	0.000	H_0 rejected at 1% level
21	Plastic Products Manufacturing	26.17	0.000	H_0 rejected at 1% level
22	Non-Metallic Mineral Products	0.01	0.932	H_0 not rejected
23	Basic Metal Industries	2.91	0.088	H_0 rejected at 10% level
24	Fabricated Metal Products	38.11	0.000	H_0 rejected at 1% level
25	Machinery & Equipment	9.93	0.002	H_0 rejected at 1% level
26	Audio & video products	27.78	0.000	H_0 rejected at 1% level
27	Electronic parts and components	42.04	0.000	H_0 rejected at 1% level
28	Electric machinery and parts	10.83	0.001	H_0 rejected at 1% level
29	Transportation Equipment	8.36	0.004	H_0 rejected at 1% level
30	Precision Instruments	1.93	0.165	H_0 not rejected
31	Miscellaneous Industrial Products	34.27	0.000	H_0 rejected at 1% level

Table 3: summary statistics on computed Technical change, RTS and TFP

Industry		TC	RTS		TFP	
		Mean	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
8	Food Manufacturing	6.83	0.94	(0.04)	6.64	(0.21)
10	Textile Mill Products	5.67	0.93	(0.04)	5.28	(0.31)
11	Wearing Apparel & Accessories	7.00	0.93	(0.03)	6.68	(0.26)
12	Leather & Fur Products	9.31	0.92	(0.04)	8.89	(0.33)
13	Wood & Bamboo Products	5.06	0.95	(0.02)	4.89	(0.14)
14	Furniture & Fixtures	7.12	0.93	(0.06)	6.78	(0.37)
15	Pulp, Paper & Paper Products	7.66	0.87	(0.03)	7.04	(0.42)
16	Printing Processing	8.31	0.91	(0.03)	7.97	(0.26)
17	Basic Chemical Matter Manufacturing	10.19	0.90	(0.04)	9.62	(0.42)
18	Chemical Products	7.99	0.91	(0.06)	7.51	(0.46)
19	Petroleum & Coal Products	6.68	0.96	(0.07)	6.41	(0.44)
20	Rubber Products Manufacturing	6.93	0.93	(0.04)	6.63	(0.24)
21	Plastic Products Manufacturing	7.03	0.92	(0.02)	6.72	(0.21)
22	Non-Metallic Mineral Products	1.30	0.92	(0.04)	0.91	(0.31)
23	Basic Metal Industries	11.72	0.92	(0.02)	11.30	(0.26)
24	Fabricated Metal Products	7.56	0.93	(0.03)	7.27	(0.21)
25	Machinery & Equipment	7.67	0.92	(0.03)	7.36	(0.25)
26	Audio & video products	10.12	0.93	(0.05)	9.66	(0.50)
27	Electronic parts and components	7.27	0.95	(0.05)	6.98	(0.38)
28	Electric machinery and parts	8.27	0.94	(0.05)	7.92	(0.37)
29	Transportation Equipment	8.08	0.94	(0.03)	7.83	(0.21)
30	Precision Instruments	9.08	0.92	(0.05)	8.66	(0.38)
31	Miscellaneous Industrial Products	9.21	0.96	(0.03)	9.06	(0.15)

NB: All indicators (TC, RTS and TFP) are computed using the parameters of a Translog production function with AR(1) error term, as described in Equations (2) and (3).

TC, as defined by Equation (4), is constant in a given 2-digit industry.

RTS and TFP, as defined by Equations (5) and (6) respectively, vary inside a given 2-digit industry.

Table 4.a : Logit estimates (propensity to innovate) – industries 08 to 20

Variables	1997 – 1999																							
	(8)		(10)		(11)		(12)		(13)		(14)		(15)		(16)		(17)		(18)		(19)		(20)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Size	0.02	(0.00)^{b}	0.01	(0.00)^{b}	0.02	(0.00)^{b}	0.02	(0.00)^{b}	0.04	(0.01)^{b}	0.03	(0.00)^{b}	0.02	(0.00)^{b}	0.03	(0.00)^{b}	0.01	(0.00)^{b}	0.04	(0.00)^{b}	0.00	(0.00)^{a}	0.02	(0.00)^{b}
Size^2	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)	-0.00	(0.00)^{b}
Age	-0.02	(0.00)^{b}	0.01	(0.01)	0.04	(0.01)^{b}	0.02	(0.01)^{a}	-0.02	(0.02)	0.00	(0.01)	0.00	(0.01)	0.00	(0.01)^{b}	-0.01	(0.01)	-0.01	(0.01)	0.00	(0.02)	-0.02	(0.01)
H	2.93	(1.00)^{b}	-0.61	(1.37)	1.35	(2.56)	-42.33	(151.7	-21.72	(18.63	-9.77	(5.87)	24.78	(3.70)^{b}	3.35	(6.98)	-16.34	(3.42)^{b}	-11.12	(3.34)^{b}	-15.47	(76.7)	70.03	(49.1)
H^2	-3.63	(1.63)^{a}	1.46	(2.12)	0.82	(2.93)	498.94	(1636.	76.75	(95.55	30.73	(15.19	-36.77	(8.40)^{b}	-0.62	(10.9)	35.13	(8.69)^{b}	27.81	(18.5)	41.46	(194.7	-576.3	(463)
Multi-plant firm	0.47	(0.12)^{b}	0.63	(0.13)^{b}	0.39	(0.18)^{a}	-0.40	(0.33)	-0.09	(0.50)	0.77	(0.26)^{b}	0.53	(0.23)^{a}	-0.82	(0.38)^{a}	0.30	(0.13)^{a}	0.21	(0.13)^{b}	0.35	(0.44)	0.84	(0.21)^{b}
Exports Tech.					2.38	(1.21)^{a}	-3.12	(6.97)									3.14	(1.11)^{a}						
Constant	-3.06	(0.13)^{b}	-3.22	(0.14)^{b}	-3.99	(0.16)^{b}	-2.38	(3.19)	-3.53	(0.54)^{b}	-3.70	(0.24)^{b}	-4.88	(0.27)^{b}	-4.06	(0.24)^{b}	-0.96	(0.22)^{b}	-1.88	(0.13)^{b}	-1.13	(5.11)	-4.18	(0.96)^{b}

Variables	2000 – 2003																							
	(8)		(10)		(11)		(12)		(13)		(14)		(15)		(16)		(17)		(18)		(19)		(20)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Size	0.01	(0.00)^{b}	0.02	(0.00)^{b}	0.01	(0.00)^{b}	0.02	(0.00)^{b}	0.04	(0.01)^{b}	0.03	(0.00)^{b}	0.02	(0.00)^{b}	0.02	(0.00)^{b}	0.01	(0.00)^{b}	0.04	(0.00)^{b}	0.01	(0.00)^{a}	0.02	(0.00)^{b}
Size^2	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)^{a}	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)^{b}	-0.00	(0.00)	-0.00	(0.00)^{b}
Age	-0.03	(0.00)^{b}	-0.01	(0.01)^{a}	0.02	(0.01)^{a}	-0.01	(0.01)	-0.06	(0.02)^{b}	-0.04	(0.02)^{b}	-0.01	(0.01)	-0.02	(0.02)^{a}	-0.01	(0.01)	-0.01	(0.01)^{a}	-0.06	(0.02)^{a}	-0.02	(0.01)
H	3.97	(1.00)^{b}	-0.51	(1.10)	0.34	(3.89)	-19.47	(25.32	-11.48	(8.99)	50.18	(45.52	15.10	(5.65)^{a}	-4.53	(14.6)	1.92	(3.94)	2.93	(4.39)	5.10	(18.46	-25.55	(50.6)
H^2	-7.98	(2.02)^{b}	0.17	(2.03)	0.85	(10.05	105.44	(137.9	29.14	(29.97	-387.9	(375.0	-25.81	(23.0)	35.58	(98.1)	-12.70	(9.77)	-65.04	(30.4)^{a}	-8.16	(50.53	227.85	(442)
Multi-plant firm	1.11	(0.10)^{b}	1.31	(0.12)^{b}	1.30	(0.21)^{b}	0.74	(0.27)^{a}	0.90	(0.38)^{a}	1.48	(0.23)^{b}	0.09	(0.28)	-0.03	(0.37)	0.72	(0.13)^{b}	0.74	(0.12)^{b}	1.56	(0.40)^{b}	1.11	(0.22)^{b}
Exports Tech.	3.39	(0.85)^{b}	3.12	(1.29)^{a}			1.42	(0.66)^{a}			4.59	(1.21)^{b}											4.35	(1.13)^{b}
Constant	-3.14	(0.14)^{b}	-3.65	(0.15)^{b}	-4.71	(0.32)^{b}	-3.09	(1.08)	-2.81	(0.42)^{b}	-4.07	(0.77)^{b}	-5.23	(0.36)^{b}	-4.76	(0.40)^{b}	-1.85	(0.32)^{b}	-2.00	(0.14)^{b}	-2.50	(1.05)^{a}	-2.52	(0.86)^{b}

a: significant at 5% level ; b: significant at 1% level.

All models also include 4-digit industry dummies

Table 4.b : Logit estimates (propensity to innovate) – industries 21 to 31

Variables	1997 – 1999																					
	(21)		(22)		(23)		(24)		(25)		(26)		(27)		(28)		(29)		(30)		(31)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Size	0.02	(0.00)[b]	0.02	(0.00)[b]	0.02	(0.00)[b]	0.03	(0.00)[b]	0.02	(0.00)[b]	0.01	(0.00)[b]	0.01	(0.00)[b]	0.02	(0.00)[b]	0.02	(0.00)[b]	0.02	(0.00)[b]	0.03	(0.00)[b]
$Size^2$	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]
Age	0.01	(0.01)	-0.01	(0.01)[a]	0.01	(0.01)	0.00	(0.01)	0.00	(0.00)	-0.01	(0.01)	-0.02	(0.01)[a]	0.02	(0.01)[a]	0.00	(0.01)	-0.02	(0.01)[a]	0.00	(0.01)
H	7.99	(5.56)	1.93	(1.99)	3.09	(1.22)[a]	0.70	(2.79)	6.12	(0.71)[b]	-5.61	(1.59)[b]	7.71	(1.36)[b]	1.73	(2.73)	1.86	(1.20)	-0.48	(5.09)	-4.90	(4.28)
H^2	-86.55	(51.5)	3.52	(6.09)	-4.08	(2.66)	-3.96	(15.8)	-8.50	(1.56)[b]	8.26	(3.29)[a]	-5.50	(3.57)	-11.55	(12.1)	-5.21	(2.80)	3.83	(16.5)	12.46	(11.9)
Multi-plant firm	0.62	(0.10)[b]	0.45	(0.13)[b]	0.67	(0.13)[b]	0.68	(0.10)[b]	0.92	(0.07)[b]	0.77	(0.13)[b]	0.39	(0.12)[b]	0.91	(0.11)[b]	0.78	(0.11)[b]	0.30	(0.19)	0.73	(0.16)[b]
Exports Tech.					-1.36	(1.35)	3.09	(0.81)[b]	0.77	(0.75)			3.55	(0.77)[b]	2.87	(0.83)[b]	3.67	(1.09)[b]	2.36	(1.36)	2.46	(1.33)
Constant	-3.79	(0.11)[b]	-3.26	(0.15)[b]	-3.63	(0.16)[b]	-3.84	(0.09)[b]	-3.40	(0.06)[b]	-0.90	(0.17)[b]	-2.50	(0.10)[b]	-3.11	(0.12)[b]	-3.16	(0.11)[b]	-2.27	(0.21)[b]	-3.55	(0.17)[b]

Variables	2000 – 2003																					
	(21)		(22)		(23)		(24)		(25)		(26)		(27)		(28)		(29)		(30)		(31)	
	C	SE	C	SE	C	SE	C	SE	C	SE	C	SE	C	SE	C	SE	C	SE	C	SE	C	SE
Size	0.02	(0.00)[b]	0.02	(0.00)[b]	0.01	(0.00)[b]	0.03	(0.00)[b]	0.03	(0.00)[b]	0.01	(0.00)[b]	0.01	(0.00)[b]	0.02	(0.00)[b]	0.02	(0.00)[b]	0.02	(0.00)[b]	0.03	(0.00)[b]
$Size^2$	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]	-0.00	(0.00)[b]
Age	-0.01	(0.01)[a]	-0.01	(0.01)	0.01	(0.01)	-0.01	(0.01)[a]	-0.01	(0.00)[a]	-0.02	(0.01)[b]	-0.01	(0.01)	0.00	(0.01)	0.01	(0.01)	-0.03	(0.01)[a]	-0.01	(0.01)
H	2.01	(2.34)	8.18	(2.60)[b]	5.36	(1.80)[b]	8.19	(3.11)[a]	7.39	(1.04)[b]	0.08	(1.20)	12.10	(1.46)[b]	9.51	(3.17)[b]	1.19	(1.60)	-1.33	(2.11)	-7.95	(4.38)
H^2	-7.35	(11.8)	-14.14	(8.66)	-9.11	(3.16)[b]	-55.83	(22.0)[a]	-13.31	(3.06)[b]	0.66	(2.40)	-13.74	(2.31)[b]	-43.36	(16.2)[a]	-6.98	(4.15)	1.85	(2.67)	21.82	(14.1)
Multi-plant firm	1.07	(0.10)[b]	0.70	(0.14)[b]	1.09	(0.14)[b]	1.03	(0.10)[b]	1.00	(0.08)[b]	0.81	(0.12)[b]	0.83	(0.11)[b]	1.49	(0.10)[b]	1.29	(0.11)[b]	0.27	(0.20)	0.98	(0.16)[b]
Exports Tech.	2.79	(0.61)[b]			2.17	(0.78)[a]	3.29	(0.59)[b]	4.32	(0.45)[b]			2.94	(0.54)[b]	1.06	(0.41)[a]	5.26	(1.02)[b]	3.90	(1.07)[b]	3.84	(0.87)[b]
Constant	-3.96	(0.14)[b]	-4.04	(0.22)[b]	-3.80	(0.20)[b]	-4.48	(0.13)[b]	-4.30	(0.10)[b]	-1.70	(0.16)[b]	-2.65	(0.13)[b]	-3.49	(0.15)[b]	-3.68	(0.14)[b]	-2.34	(0.24)[b]	-3.22	(0.19)[b]

a: significant at 5% level ; b: significant at 1% level.

All models also include 4-digit industry dummies

Table 5: ATT estimates using Logit to compute PS (contemporaneous specification)

Industry	Matching method = Nearest neighbour				Matching method : kernel			
	1997 – 1999		2000 - 2003		1997 – 1999		2000 - 2003	
	ATT	*S.E.*	*ATT*	*S.E.*	*ATT*	*S.E.*	*ATT*	*S.E.*
(8)	-0.013	(0.015)	-0.050	(0.017)[b]	-0.031	(0.011)[b]	-0.063	(0.013)[b]
(10)	-0.064	(0.029)[a]	-0.079	(0.034)[a]	-0.111	(0.020)[b]	-0.094	(0.024)[b]
(11)	-0.070	(0.025)[b]	-0.076	(0.037)[a]	-0.118	(0.018)[b]	-0.114	(0.027)[b]
(12)	-0.208	(0.051)[b]	-0.174	(0.055)[b]	-0.166	(0.029)[b]	-0.189	(0.037)[b]
(13)	-0.009	(0.021)	0.020	(0.019)	-0.011	(0.014)	0.007	(0.014)
(14)	-0.121	(0.063)[a]	-0.151	(0.076)[a]	-0.214	(0.047)[b]	-0.221	(0.058)[b]
(15)	-0.044	(0.075)	-0.127	(0.084)	-0.087	(0.052)[a]	-0.148	(0.061)[b]
(16)	0.006	(0.042)	-0.028	(0.064)	-0.066	(0.027)[b]	-0.124	(0.047)[b]
(17)	-0.183	(0.038)[b]	-0.104	(0.046)[a]	-0.164	(0.026)[b]	-0.137	(0.029)[b]
(18)	-0.110	(0.033)[b]	-0.130	(0.035)[b]	-0.125	(0.023)[b]	-0.143	(0.023)[b]
(19)	-0.040	(0.138)	-0.011	(0.104)	-0.191	(0.096)[a]	-0.024	(0.076)
(20)	-0.099	(0.035)[b]	-0.064	(0.039)	-0.114	(0.027)[b]	-0.092	(0.030)[b]
(21)	-0.063	(0.017)[b]	-0.121	(0.018)[b]	-0.126	(0.011)[b]	-0.158	(0.013)[b]
(22)	-0.036	(0.025)	-0.040	(0.030)	-0.078	(0.018)[b]	-0.053	(0.023)[a]
(23)	-0.003	(0.023)	0.018	(0.025)	-0.028	(0.016)[a]	-0.010	(0.019)
(24)	-0.051	(0.013)[b]	-0.078	(0.015)[b]	-0.080	(0.009)[b]	-0.103	(0.011)[b]
(25)	-0.099	(0.014)[b]	-0.130	(0.016)[b]	-0.138	(0.010)[b]	-0.157	(0.011)[b]
(26)	-0.218	(0.031)[b]	-0.261	(0.041)[b]	-0.218	(0.023)[b]	-0.293	(0.030)[b]
(27)	-0.145	(0.033)[b]	-0.244	(0.048)[b]	-0.116	(0.021)[b]	-0.179	(0.027)[b]
(28)	-0.107	(0.032)[b]	-0.166	(0.034)[b]	-0.131	(0.021)[b]	-0.186	(0.024)[b]
(29)	-0.069	(0.020)[b]	-0.101	(0.022)[b]	-0.089	(0.013)[b]	-0.105	(0.015)[b]
(30)	-0.076	(0.038)[a]	-0.193	(0.045)[b]	-0.107	(0.026)[b]	-0.190	(0.037)[b]
(31)	-0.025	(0.014)[a]	0.006	(0.021)	-0.021	(0.010)[a]	-0.020	(0.014)

Table 6: checking of the balancing property (contemporaneous specification)

Industry	1997 - 1999			2000 - 2003		
	Before matching	*After Matching (n.n.)*	*After Matching (kernel)*	*Before matching*	*After Matching (n.n.)*	*After Matching (kernel)*
(8)	33.06	13.95	12.31	28.38	12.51	8.91
(10)	32.09	10.12	8.44	32.96	10.48	10.17
(11)	34.80	8.22	8.27	35.03	4.98	9.09
(12)	21.91	15.98	2.09	27.21	14.31	11.57
(13)	26.82	11.32	9.72	34.35	13.23	11.34
(14)	35.62	18.48	19.09	36.84	8.09	12.67
(15)	61.28	12.66	12.91	60.64	7.28	8.00
(16)	24.33	4.97	9.26	34.87	5.83	7.24
(17)	31.09	11.84	7.87	35.05	13.36	11.25
(18)	33.61	3.53	5.47	36.45	6.13	5.00
(19)	48.06	30.46	14.08	46.20	15.35	7.17
(20)	52.40	9.85	10.15	54.70	20.19	19.86
(21)	23.24	12.22	9.44	22.39	10.25	8.24
(22)	38.16	11.22	7.30	41.51	9.86	8.72
(23)	26.99	11.88	11.11	26.61	12.60	9.48
(24)	29.35	8.09	7.68	30.12	8.56	7.61
(25)	22.75	6.84	5.05	34.17	8.36	5.84
(26)	24.87	12.84	11.53	29.84	11.19	12.33
(27)	34.99	19.19	15.78	32.04	14.89	15.71
(28)	31.72	7.68	7.78	38.54	10.71	9.54
(29)	28.93	9.01	9.41	35.26	7.11	10.81
(30)	19.40	9.24	5.84	23.03	12.56	10.13
(31)	30.66	12.86	7.18	34.16	13.64	14.28

Table 7: Mantel-Haenszel unobserved heterogeneity test (contemporaneous specification)

Industry	Matching method = Nearest neighbour								Matching method : kernel							
	1997 - 1999				2000 - 2007				1997 - 1999				2000 - 2007			
	Q_{mh}^{+}	Q_{mh}^{-}	p_{mh}^{+}	p_{mh}^{-}	Q_{mh}^{+}	Q_{mh}^{-}	p_{mh}^{+}	p_{mh}^{-}	Q_{mh}^{+}	Q_{mh}^{-}	p_{mh}^{+}	p_{mh}^{-}	Q_{mh}^{+}	Q_{mh}^{-}	p_{mh}^{+}	p_{mh}^{-}
(8)	-0.03	-0.03	0.51	0.51	-0.03	-0.03	0.51	0.51	-0.02	-0.02	0.51	0.51	-0.02	-0.02	0.51	0.51
(10)	-0.03	-0.03	0.51	0.51	-0.04	-0.04	0.52	0.52	-0.02	-0.02	0.51	0.51	-0.03	-0.03	0.51	0.51
(11)	-0.04	-0.04	0.52	0.52	-0.06	-0.06	0.52	0.52	-0.03	-0.03	0.51	0.51	-0.04	-0.04	0.52	0.52
(12)	-0.06	-0.06	0.52	0.52	-0.06	-0.06	0.52	0.52	-0.04	-0.04	0.52	0.52	-0.04	-0.04	0.52	0.52
(13)	-0.09	-0.09	0.53	0.53	-0.08	-0.08	0.53	0.53	-0.06	-0.06	0.52	0.52	-0.06	-0.06	0.52	0.52
(14)	-0.06	-0.06	0.52	0.52	-0.06	-0.06	0.53	0.53	-0.04	-0.04	0.52	0.52	-0.04	-0.04	0.52	0.52
(15)	-0.05	-0.05	0.52	0.52	-0.06	-0.06	0.53	0.53	-0.04	-0.04	0.51	0.51	-0.04	-0.04	0.52	0.52
(16)	-0.06	-0.06	0.52	0.52	-0.07	-0.07	0.53	0.53	-0.04	-0.04	0.52	0.52	-0.05	-0.05	0.52	0.52
(17)	-0.04	-0.04	0.51	0.51	-0.04	-0.04	0.51	0.51	-0.02	-0.02	0.51	0.51	-0.03	-0.03	0.51	0.51
(18)	-0.03	-0.03	0.51	0.51	-0.03	-0.03	0.51	0.51	-0.02	-0.02	0.51	0.51	-0.02	-0.02	0.51	0.51
(19)	-0.11	-0.11	0.54	0.54	-0.10	-0.10	0.54	0.54	-0.08	-0.08	0.53	0.53	-0.07	-0.07	0.53	0.53
(20)	-0.05	-0.05	0.52	0.52	-0.06	-0.06	0.52	0.52	-0.04	-0.04	0.51	0.51	-0.04	-0.04	0.51	0.51
(21)	-0.03	-0.03	0.51	0.51	-0.03	-0.03	0.51	0.51	-0.02	-0.02	0.51	0.51	-0.02	-0.02	0.51	0.51
(22)	-0.03	-0.03	0.51	0.51	-0.04	-0.04	0.52	0.52	-0.02	-0.02	0.51	0.51	-0.03	-0.03	0.51	0.51
(23)	-0.04	-0.04	0.52	0.52	-0.04	-0.04	0.52	0.52	-0.03	-0.03	0.51	0.51	-0.03	-0.03	0.51	0.51
(24)	-0.02	-0.02	0.51	0.51	-0.03	-0.03	0.51	0.51	-0.02	-0.02	0.51	0.51	-0.02	-0.02	0.51	0.51
(25)	-0.02	-0.02	0.51	0.51	-0.02	-0.02	0.51	0.51	-0.01	-0.01	0.51	0.51	-0.01	-0.01	0.51	0.51
(26)	-0.03	-0.03	0.51	0.51	-0.03	-0.03	0.51	0.51	-0.02	-0.02	0.51	0.51	-0.02	-0.02	0.51	0.51
(27)	-0.03	-0.03	0.51	0.51	-0.03	-0.03	0.51	0.51	-0.02	-0.02	0.51	0.51	-0.02	-0.02	0.51	0.51
(28)	-0.03	-0.03	0.51	0.51	-0.03	-0.03	0.51	0.51	-0.02	-0.02	0.51	0.51	-0.02	-0.02	0.51	0.51
(29)	-0.03	-0.03	0.51	0.51	-0.03	-0.03	0.51	0.51	-0.02	-0.02	0.51	0.51	-0.02	-0.02	0.51	0.51
(30)	-0.04	-0.04	0.52	0.52	-0.04	-0.04	0.52	0.52	-0.03	-0.03	0.51	0.51	-0.03	-0.03	0.51	0.51
(31)	-0.04	-0.04	0.51	0.51	-0.04	-0.04	0.52	0.52	-0.03	-0.03	0.51	0.51	-0.03	-0.03	0.51	0.51

Q_{mh} : Mantel-Haenszel statistic (+ : overestimation of treatment effect; -: underestimation of treatment effect)

p_{mh} : significance level (+ : overestimation of treatment effect; -: underestimation of treatment effect)

Table 8: ATT estimates (lagged specification)

Industry	Matching method = Nearest neighbour				Matching method : kernel			
	1997 – 1999		2000 - 2003		1997 – 1999		2000 - 2003	
	ATT	*S.E.*	*ATT*	*S.E.*	*ATT*	*S.E.*	*ATT*	*S.E.*
(8)	0.0002	(0.026)	-0.106	(0.033)[b]	-0.02	(0.019)	-0.082	(0.027)[b]
(10)	-0.084	(0.045)[a]	-0.047	(0.057)	-0.15	(0.034)[b]	-0.450	(0.024)[b]
(11)	-0.097	(0.046)[a]	-0.035	(0.083)	-0.12	(0.036)[b]	-0.084	(0.057)
(12)	-0.266	(0.079)[b]	-0.301	(0.102)[b]	-0.21	(0.050)[b]	-0.251	(0.074)[b]
(13)	0.009	(0.033)	-0.002	(0.041)	0.00	(0.025)	-0.004	(0.029)
(14)	-0.119	(0.106)	-0.301	(0.138)[a]	-0.20	(0.065)[b]	-0.318	(0.106)[b]
(15)	-0.091	(0.115)	-0.185	(0.134)	-0.14	(0.085	-0.177	(0.103)[a]
(16)	0.040	(0.082)	-0.064	(0.138)	-0.08	(0.050)	-0.213	(0.106)[a]
(17)	-0.029	(0.068)	-0.158	(0.076)[a]	-0.13	(0.045)[b]	-0.089	(0.053)[a]
(18)	-0.151	(0.052)[b]	-0.228	(0.058)[b]	-0.13	(0.040)[b]	-0.160	(0.043)[b]
(19)	-0.123	(0.154)	-0.216	(0.214)	-0.06	(0.106)	-0.085	(0.147
(20)	-0.143	(0.053)	-0.175	(0.064)[b]	-0.14	(0.045)[b]	-0.185	(0.057)[b]
(21)	-0.065	(0.029)[a]	-0.132	(0.041)[b]	-0.13	(0.020)[b]	-0.154	(0.029)[b]
(22)	-0.001	(0.044)	0.037	(0.065)	-0.06	(0.032)[a]	-0.002	(0.049)
(23)	-0.018	(0.037)	-0.038	(0.048)	-0.05	(0.029)	-0.040	(0.035)
(24)	-0.078	(0.021)[b]	-0.067	(0.034)[a]	-0.10	(0.016)[b]	-0.089	(0.024)[b]
(25)	-0.105	(0.024)[b]	-0.165	(0.030)[b]	-0.16	(0.017)[b]	-0.223	(0.022)[b]
(26)	-0.272	(0.055)[b]	-0.510	(0.078)[b]	-0.30	(0.043)[b]	-0.471	(0.056)[b]
(27)	-0.120	(0.057)[a]	-0.349	(0.081)[b]	-0.11	(0.045)[b]	-0.345	(0.050)[b]
(28)	-0.052	(0.049)	-0.157	(0.066)[b]	-0.08	(0.036)[a]	-0.277	(0.042)[b]
(29)	-0.015	(0.035)	-0.195	(0.047)[b]	-0.08	(0.022)[b]	-0.163	(0.026)[b]
(30)	-0.061	(0.069)	-0.197	(0.092)[a]	-0.12	(0.046)[b]	-0.250	(0.076)[b]
(31)	0.015	(0.031)	-0.052	(0.047)	-0.02	(0.021)	-0.056	(0.029)[a]

Table 9: checking of the balancing property (lagged specification)

Industry	1997 - 1999			2000 - 2003		
	Before matching	*After Matching (n.n.)*	*After Matching (kernel)*	*Before matching*	*After Matching (n.n.)*	*After Matching (kernel)*
(8)	32.59	13.32	13.34	30.81	12.43	13.08
(10)	35.31	8.43	6.41	42.32	12.79	16.31
(11)	33.91	12.84	8.86	50.49	25.37	14.16
(12)	23.30	21.34	2.47	32.53	22.76	22.88
(13)	27.42	12.70	4.35	48.48	17.03	19.66
(14)	39.87	26.06	19.59	50.34	21.54	17.01
(15)	60.85	8.71	13.83	69.05	19.44	12.18
(16)	24.27	10.19	14.86	47.56	13.94	14.99
(17)	30.27	13.30	11.63	39.84	14.05	10.75
(18)	33.71	9.73	5.62	41.90	10.40	8.62
(19)	42.78	28.03	7.33	51.04	65.21	21.95
(20)	50.92	6.60	12.66	63.20	28.79	31.57
(21)	24.37	16.54	9.38	31.41	13.38	13.06
(22)	40.20	15.57	12.70	57.44	20.78	17.87
(23)	25.50	13.12	13.10	32.37	10.73	8.63
(24)	26.93	6.27	8.44	39.56	10.03	9.83
(25)	26.55	9.56	6.04	32.62	20.47	19.51
(26)	28.46	14.10	12.09	31.48	15.92	14.90
(27)	34.67	19.63	19.60	36.15	16.39	16.87
(28)	29.82	6.59	9.35	41.09	7.80	12.39
(29)	27.84	19.65	14.45	38.71	23.20	18.30
(30)	20.98	14.98	7.37	24.00	19.90	14.29
(31)	35.72	16.95	18.93	38.91	16.82	15.34