Endogenous Product versus Process Innovation and a Firm's Propensity to Export*

Sascha O. Becker† and Peter H. Egger‡

November 2, 2006

Abstract

This paper provides an empirical analysis of the effects of new product versus process innovations on export propensity at the firm level. Product innovation is a key factor for successful market entry in models of creative construction and Schumpeterian growth. Process innovation helps securing a firm's market position given the characteristics of its product supply. Both modes of innovation are expected to raise a firm's propensity to export. According to new trade theory, we conjecture that product innovation is relatively more important in that regard. We investigate these hypotheses in a rich survey panel data set with information about new innovations of either type. With a set of indicators regarding innovation motives and impediments and continuous variables at the firm and industry level at hand, we may determine the probability to launch new innovations and their impact on export propensity at the firm level through a double treatment approach.

Key words: Product innovation; Process innovation; Propensity to export; Multiple treatment effects estimation

JEL classification: F1, O3, L1.

---

* *Acknowledgements*: To be added.

† *Affiliation:* Center for Economic Studies at the University of Munich, CESifo and IZA. *Address:* CES, University of Munich, Department of Economics, Schackstrasse 4, 80539 Munich, Germany. E-mail: sbecker@lmu.de

‡ *Affiliation:* Ifo Institute, University of Munich, CESifo, and Leverhulme Centre for Research on Globalisation and Economic Policy (GEP) at the University of Nottingham. *Address:* Ifo Institute of Economic Research, Poschingerstrasse 5, 81679 Munich, Germany. E-mail: egger@ifo.de.

1 Introduction

Research on innovation has for long been at the heart of three different fields of the profession: macro-economics, international economics, and industrial economics. Two central insights can be thought of unifying these literatures, namely that innovation is endogenous at the firm-level, and it is undertaken for the sake of productivity gains that secure a firm's market position against its less successful rivals.

After decades of fruitful work on the nexus between innovation and productivity growth, we are now observing a new wave of interest in the role of innovation for a firm's export performance. Research on the latter is developed at the intersection of international economics and industrial organization. Again, related economic theory understands a firm's innovation to be central for its productivity, yet productivity gains do not only affect a firm's domestic performance vis-à-vis its domestic competitors but they enable it to penetrate foreign markets by serving consumers abroad through exports. Hence, that literature views innovation as a prerequisite of surviving the fiercer competition at global markets. These hypotheses found broad confirmation in recent empirical work.

While earlier theoretical work on productivity/economic growth implicitly defines innovation as *product innovation*, a few recent attempts distinguish between product and process innovation. The latter distinction is accounted for in a similarly small body of empirical work, where either kind of innovation is then treated as exogenous or at least as predetermined.

This paper aims at contributing to previous empirical work on innovation and exports by (i) distinguishing between the effects of product and process innovation on export propensity, and, at the same time, (ii) by taking full account of the endogeneity of innovation of either kind.

The remainder of the paper is organized as follows. The next section provides an overview of earlier theoretical and empirical work on innovation to motivate determinants of innovations and derive hypotheses about their consequences for productivity and export propensity. Section 3 elaborates on the empirical framework for estimating the impact of two endogenous modes of innovation on export propensity. Section 4 summarizes the main features of our survey data. The empirical findings are presented in Section 5, they are discussed and their sensitivity is investigated in Section 6, and the last section concludes with a summary of the central findings.

2 Previous research and the contribution of this paper

In the subsequent discussion of previous, innovation-related economic work, it is useful to distinguish between theoretical and empirical research on the issue.

2.1 Economic theory on innovation

There is a sizeable body of theoretical work that elaborates on the determinants of innovation and their consequences for productivity and economic growth and, to a lesser extent, for exports.

Macro-economists stress the importance of innovation in new products as a prerequisite for economic growth. As indicated before, innovation is endogenous itself and firms innovate more likely in large economies (where fixed costs can be covered more easily), if the (exogenous) productivity in research labs is high, product markets are competitive, and if consumers value a large variety and/or a high quality of available products (see Grossman and Helpman, 1991, chapters 3 and 4). Implicitly, most of the related studies confine their interest to product innovation. Only recently, macro-economists explore the potential differences between product and process innovations for income, focusing on heterogeneous agents and technological unemployment (Foellmi and Zweimller, 2005). One key finding in the latter branch of work is that process innovation may lead to technological unemployment in the short-to-medium run which may be offset by product innovation in the long-run. While both process and product innovation spur aggregate income, product innovation is preferable by avoiding the adverse effects of technological unemployment.

International economic theory spots the role of product innovation for trade in open economy growth models (Dollar, 1986; Jensen and Thursby, 1987; Grossman and Helpman, 1989, 1990, 1991, chapters 9-11; Segerstrom, Anant, and Dinopoulos, 1990). As in closed-economy models of endogenous growth, market size, the productivity of research labs, consumer preferences favoring a larger variety and/or a higher quality of products, and product market competition are key determinants of innovation. An economy's openness to trade additionally fosters product market competition and, hence, creates an incentive for a firm to innovate. In turn, innovation is a prerequisite for firms to gain access to foreign consumer bases via exports. The latter establishes the hypothesis of innovation-driven exports. In recent dynamic models with firms that exhibit heterogeneous productivity levels and, hence, heterogeneous marginal production costs (Jovanovich, 1982; Hopenhayn, 1992; Melitz, 2003; Grossman, Helpman, and Szeidl, 2006) investment in firm-specific assets leads to a selection of firms: the least productive ones do not participate at the market at all and the most productive ones supply consumers not only at home but also abroad (through exports), while those with an intermediate productivity only face demand from domestic consumers. There, investment in firm-specific assets (to be associated with product innovation, see Spence, 1984) and a high corresponding outcome (i.e., a high total factor productivity) are the key determinants of a firm's export propensity.

Research in industrial economics provided pioneering results on the role of marginal cost-reducing innovations (i.e., expenditures for research and development for the sake of process innovation) in international oligopoly models more than two decades ago (Spencer and Brander, 1983). A higher investment in such process innovations increases a firm's domestic and foreign output. However, this eventually leads to an excessive amount of innovations of that kind. The equilibrium level of (process) innovation expenditures increases with domestic and foreign market size, and it declines in the level of trade costs and the degree of product market competition (i.e., the number of competitors in the market). Subsequent research established insights on the relationship between process innovation and competitive pressure at the local (Martin, 1993) and the global level (Baily and Gersbach, 1995). More recently, an explicit treatment of product versus process innovations and the role of competitive pressure has been delivered by Boone (2000). The impact of product market competition on a firm's product and process innovations crucially depends on the firm's efficiency relative to its opponents. When assuming that the aggregate efficiency can be measured by the (inverse of) average production costs, then, Boone's (2000) analysis suggests that a higher level of competitive pressure cannot increase product and process innovation at the same time. Rather, an increase in the competitive pressure may increase the efficiency of each surviving firm but lead to the exit of less productive ones, which is associated with a decline in product innovation. Overall, a positive impact of competitive pressure on process innovation is a possible, yet not a necessary outcome.

2.2 Empirical work on the determinants and effects of innovation

Numerous previous empirical studies point to a positive impact of innovation on exports at the firm- or plant-level. Some of the related studies rely on R&D expenditures as an indirect measure of innovations (Hirsch and Bijaoui, 1985; Kumar and Siddharthan, 1994; Braunerhjelm, 1996; Basile, 2001) and a smaller number of studies employs survey data with explicit information on the actual innovations based on survey data (Wakelin, 1998; Bernard and Jensen, 1999; Roper and Love, 2002; Cassiman and Martínez-Ros, 2004; Lachenmaier and W¨ßmann, 2006). Overall, these studies point to a strong positive impact of innovations on exports.[1] While most of the mentioned studies were carried out in cross-sectional data-sets, there is evidence of a positive impact of innovation on exports (or export growth) also in panel data-sets (Hirsch and Bijaoui, 1985; Cassiman and Martínez-Ros, 2004).

Surprisingly, in as much as the aforementioned theoretical models establish an endogenous determination of innovations and economic theory on innovation and exports addresses their simultaneous determination (Hughes, 1998), empirical micro-econometric work on innovation-driven exports tends to model the selection of firms into innovations as a random (or exogenous) process. Two exceptions in the latter regard are Cassiman and Martínez-Ros (2004) and Lachenmaier and W¨ßmann (2006). Both studies exploit information from panel data. Cassiman and Martínez-Ros (2004) focus on innovations as such and treat them as predetermined variables (hence, they use once-lagged instead of contemporaneous innovations in the export regressions). Lachenmaier and W¨ßmann (2006) apply instrumental-variable procedures to account for the potential endogeneity of innovations. One of their major findings is that innovations are indeed endogenous and their exogenous treatment leads to a largely upward-biased estimate of the impact of innovations on firm-level exports.

2.3 Contribution of this paper

This paper departs from the strategy adopted in previous micro-econometric work on the innovation-driven exports hypothesis in two important ways.

[1] A smaller number of studies that employed the less preferable R&D expenditures as an indirect measure of innovations lacked to find such a positive impact (see Cassiman and Martínez-Ros, 2004, for a survey).

First, it explicitly distinguishes between product and process innovations in the analysis and, second, it accounts for their endogeneity by allowing for an endogenous selection of firms into product and process innovations.[2] In contrast to earlier work, we use matching techniques for multiple binary treatments – in our case, new product and/or process innovations versus no innovations at all – to account for self-selection of firms into either type of innovation.

3 Empirical framework

In the subsequent analysis we assume that, after controlling for a set of observable variables, treatment participation does not depend on treatment outcome. The latter is also referred to as the assumption of conditional mean-independence (see Wooldridge, 2002). One strategy of exploiting this assumption for the purpose of treatment effect identification is propensity score matching (see Angrist, 1998; Dehejia and Wahba, 1999, 2002, Heckman, Ichimura, and Todd; 1997, 1998; Lechner 1999; Heckman, LaLonde, and Smith, 1999, provide a survey).

Since our data set allows us to disentangle product innovation from process innovation – hence, there are two treatment indicators at the firm level –, we have to depart from the strategy typically applied in models with a simple binary treatment variable. Obviously, the choice set from a firm's perspective can not be captured by a single binary indicator, but rather it spans a 2×2 matrix of mutually exclusive innovation-related treatments. Let us use superscripts 0, d, and c to indicate the cases of no treatment, product innovation, and process innovation, respectively. Then, the four mutually exclusive

[2]Cohen and Klepper (1996) formulate and test an interesting model of the determinants of product as well as process innovation in a cross-sectional data-set of 587 U.S. firms. They find that large firms, in accordance with their model, have a greater incentive to pursue both process and product innovations. However, these firms face a relatively larger incentive to undertake process and more incremental innovations as compared to small ones. Martínez-Ros (2000) provides an empirical analysis of the determinants of product and process innovations in a Spanish firm-level data-set. Neither of these studies considers the impact of these two modes of endogenous innovations on exports. Basile (2001) looks at the effect of product and process innovations (measured by two different R&D expenditure modes) on exports, but he treats innovations as exogenous. The paper by Lachenmaier and Wößmann (2006) also distinguish between product and process innovations, but only in a single specification of the sensitivity analysis, and it fails to estimate their impact on exports significantly at conventional levels.

treatments are $0,0$ (the *no treatment* case), $d,0$ (new product innovations only), $0,c$ (new process innovations only), and d,c (both new product and new process innovations).[3] A matching approach with multiple treatments has been derived by Lechner (1999).[4]

For convenience, let us refer to the *no treatment* outcome as $Y^{0,0}$ (i.e., the corresponding export propensity as captured by a binary firm-level export indicator). The remaining possible outcomes are $Y^{d,0}$, $Y^{0,c}$, and $Y^{d,c}$, respectively. Let us use superscripts m and l as running indices for the four treatments to determine three different types of treatment effects (see Lechner, 1999). The expected average effect of treatment m relative to treatment l for a firm drawn randomly from the population is defined as

$$\gamma^{m,l} = E(Y^m - Y^l) = E(Y^m) - E(Y^l). \tag{1}$$

The expected average effect of treatment m relative to treatment l for a firm randomly selected from the group of firms participating in either m or l is defined as

$$\alpha^{m,l} = E(Y^m - Y^l|S = m,l) = E(Y^m|S = m,l) - E(Y^l|S = m,l), \tag{2}$$

where S is the assignment indicator, defining whether a firm receives treatment m or l. Finally, the expected average effect of treatment m relative to treatment l for a unit that is randomly selected from the group of firms participating in m only is defined as

$$\theta^{m,l} = E(Y^m - Y^l|S = m) = E(Y^m|S = m) - E(Y^l|S = m). \tag{3}$$

Note that both $\gamma^{m,l}$ and $\alpha^{m,l}$ are symmetric in the sense that $\gamma^{m,l} = -\gamma^{l,m}$ and $\alpha^{m,l} = -\alpha^{l,m}$, whereas $\theta^{m,l}$ is not, so that $\theta^{m,l} \neq -\theta^{l,m}$.

Estimates of the average treatment effects can be obtained as follows. First, the response probabilities for each treatment can be estimated either by a bivariate probability model (it is customary to use a logit or a probit model). Denote the estimated response probabilities that are a function of the vector of observable variables $\mathbf{x}$ as $\hat{P}^m(\mathbf{x})$ for $m = (0,0); (d,0); (0,c); (d,c)$, respectively. Second, estimate the expectation $E(Y^m|S = m)$ by $E\{E[Y^m|\hat{P}^m(\mathbf{x})S =$

[3] Notice that the underlying choices are unordered, here.

[4] See also Lee (2005) for a recent discussion of this framework.

$m]|S \neq m\}$ and the expectation $E(Y^l|S = m)$ by $E\{E[Y^l|\hat{P}^l(\mathbf{x}), \hat{P}^m(\mathbf{x})S = l]|S = m\}$. We apply nearest-neighbor matching (each treated firm is compared to a single control unit), radius matching (each treated firm is compared to all firms within a certain radius around its propensity score), and kernel matching (each treated unit is compared to all untreated firms in a certain area around the propensity score depending on the bandwidth of the kernel, but inversely weighted with their difference in propensity score to the treated unit). The average treatment effect (i.e., the outer expectation above) is estimated as the average of the difference in outcomes between the treated and the control units.

We pursue two alternative estimates of the standard error of each of the treatment effects. First, we compute analytic standard errors as in Lechner (2001). The analytic standard errors for the three treatment effect concepts are

$$
\begin{aligned}
Var(\hat{\theta}^{m,l}) &= \frac{1}{N^m} Var(Y^m|S = m) + \frac{\sum_{i \in l} (w_i^m)^2}{(\sum_{i \in l} w_i^m)^2} Var(Y^l|S = l), \quad (4) \\
Var(\hat{\alpha}^{m,l}) &= \sum_{i \in m} \left[\frac{1 + w_i^l}{N^m + N^l} \right]^2 Var(Y^m|S = m) \\
&+ \sum_{i \in l} \left[\frac{1 + w_i^m}{N^m + N^l} \right]^2 Var(Y^l|S = l), \quad (5) \\
Var(\hat{\gamma}^{m,l}) &= \sum_{i \in m} \left[\sum_{j=0}^{M} \frac{w_i^j}{n} \right]^2 Var(Y^m|S = m) \\
&+ \sum_{i \in l} \left[\sum_{j=0}^{M} \frac{w_i^j}{n} \right]^2 Var(Y^l|S = l). \quad (6)
\end{aligned}
$$

In empirical applications, these analytical standard errors may deviate considerably from their small-sample-counterparts. Therefore, we alternatively compute sub-sampling-based standard errors following Politis, Romano, and Wolf (1999). As shown by Abadie and Imbens (2006) these give reliable variance estimates of treatment effects even in small samples.

4 Data

Our data are based on the Ifo Innovation Survey that is conducted annually by the Ifo Institute, covering more than 1,000 firms in Germany per year. The survey asks about the structure of innovations at the firm level. In particular, it collects information about process versus product innovation activities and about export status. Furthermore, the survey explicitly covers questions relating to exogenous innovation impulses and obstacles as well as other firm-level characteristics. Beyond that, there is an industry indicator that allows us to link industry characteristics to the micro-level data.

4.1 Dependent variables

Regarding the dependent variables, the database provides information on whether a firm has exported and applied new product innovations or process innovations over the last six months or not. The corresponding questions that we rely on in our analysis can be translated as follows:

- *We did not export (in year t).* As our outcome variable, we construct a dummy variable that takes a value of one if firms export and zero if they do not.

- *In the year t we have introduced (or started but not yet finished) new product innovations. In the year t we have introduced (or started but not yet finished) new process innovations.* We use the answers to these questions to construct two dummy variables, one that takes on a value if new product innovations were undertaken in year t and zero else, and the other is constructed in the same way but for process innovations.

Overall, there are $1,537$ firms and $4,499$ observations in our database. Note that every observation covers three years of data because our outcome is measured in $t+1$, the treatment in t and pre-treatment variables in $t-1$. A cross-tabulation for export propensity and the two innovation indicators is provided in Table 1. The entries can be summarized as follows. First, 80.00 percent of the firms in our sample conduct exports. The high fraction of exporters is not surprising, since, by design, the survey covers mainly large manufacturing firms. Second, 61.96 percent of the firms innovate (i.e., they receive treatments $(d, 0)$, $(0, c)$, or (d, c)). Of those, 23.57 percent conduct

Table 1: Exports and innovations: a summary

Export	Product innovation 0	1	Total
0	638	262	900
1	1,322	2,277	3,599
Total	1,960	2,539	4,499

Export	Process innovation 0	1	Total
0	661	239	900
1	1,707	1,892	3,599
Total	2,368	2,131	4,499

Source: Ifo Innovation Survey, 1994-2004.

product innovations only $(d, 0)$, 8.93 percent conduct process innovations only $(0, c)$, and 67.50 percent do both (d, c).

4.2 Independent variables

Beyond the information for the dependent variables in our analysis, the survey asks about a set of incentives/impulses and obstables/impediments to innovation. Of those, in our empirical model, only the following four impediments exert a significant impact on a firm's probability to innovate: lacking own capital; lacking external capital; long amortization period; imperfect opportunities to cooperate with public or academic institutions. For these obstacles to innovation, multiple answers are possible and they are numerical: 1 (not important at all); 2 (not very important); 3 (important); 4 (extremely important). We generate a binary variable for each impediment and classify 3 and 4 as one and 1 and 2 as zero.

Furthermore, we include lagged logarithms of sales and employment at the firm level as two separate regressors. In addition to these firm-level determinants we use characteristics that vary across NACE 2-digit industries published by EUROSTAT (NewCronos Database). In particular, we employ German data on industry employment (to capture the size of an industry). Furthermore, we use inverse-distance weighted industry value added and wages of the EU14 economies. There, each of the two explanatory variables x for industry i and time t is weighted across the 14 EU member countries as of 1995 excluding Germany according to $\tilde{x}_{it} = \sum_j^{14}[(x_{ijt}d_j/\sum_j d_j]$ with d_j denoting an economy j's inverse distance to Germany.[5] These variables control for both a firm's competitive pressure at the domestic and the Western European foreign markets and they approximate the size of the market there. For instance, the inverse-distance weighted value added can be interpreted as a measure of the foreign potential supply. The higher the latter, the stronger we conjecture competition to be for German producers. By way of contrast, the higher the weighted foreign wage costs are, the lower we expect the competitive pressure for German producers to be.[6] Table 2 summarizes mean and standard deviation of all covariates.

5 Estimation results

Tables 3 and 4 presents the results of two multivariate probability models determining a representative firm's choice of product and/or process innovation: a bivariate probit model (assuming a bivariate normal cumulative density function of the latent outcome variable) and a multinomial logit model (assuming a logistic cumulative density function, respectively).

The estimates and test statistics reported in the table suggest the following conclusions. First, the value of the log-likelihood under the bivariate probit model is -4312.14 while that one under the multinomial logit is -4241.27. Davidson and MacKinnon (2004) suggest selecting among such non-nested, non-linear probability models according to a likelihood ratio statistic based on twice the absolute difference in the corresponding log-likelihoods (LL): $LR = 2|LL_{probit} - LL_{logit}|$. This test statistic is distributed as $\chi^2(1)$. Following this device, we find that the statistic amounts to 141.71, which is significant at the one percent level. Hence, the data are more appropriately

[5] The notion that trade decreases in distance (i.e., increases in inverse distance) is one of the most robust stylized facts in empirical research in international economics (see Leamer and Levinsohn, 1995).

[6] We experimented with alternative specifications, where we also used industry-level wages and value added in Germany. However, it turns out that these do not contribute significantly once we control for their weighted EU14 counterparts.

Table 2: Descriptive statistics

	mean	s.d.
Firm-level variables		
ln(Turnover) in $t-1$	10.100	1.972
ln(Turnover per worker) in $t-1$	5.350	1.024
Indic.: Lacking own capital	.293	.455
Indic.: Lacking external capital	.221	.415
Indic.: Long amortization period	.331	.471
Indic.: Imperfect cooperation poss.	.150	.357
Sector-level variables		
for Germany		
ln(Value-added) in $t-1$	9.608	.957
ln(Value-added per worker) in $t-1$	-3.156	.204
ln(Unit labor cost) in $t-1$	-1.439	.245
for EU14		
ln(Value-added) in $t-1$	7.915	.812
ln(Value-added per worker) in $t-1$	-3.000	.299
ln(Unit labor cost) in $t-1$	-1.795	.232

Source: Ifo Innovation Survey, 1994-2004.

described by the multinomial logit model, which we also use in the sequel for matching.

Furthermore, the test statistics indicate that domestic industry variables and weighted EU14 industry variables are group-wise and jointly significant at the one percent level in the model. Similarly, the included innovation impediments are jointly significant.

To check whether propensity score matching achieves better balancing of the variables in our model, we calculate the reduction of the median absolute standardized bias in the observables included in the selection models between the treated firms and *all* control units versus the treated and the *matched* control units. While there is no firm rule of thumb, the statistics literature suggests that the remaining bias should definitely be smaller than 20 percent

(Rosenbaum and Rubin, 1985). In our case, the median bias between the treated and the matched control units amounts to about 8 percent, which seems reasonable. In the case of statistically significant effects, the bias reduction is even larger. For instance, for the effect (d, c) versus $(0, 0)$, the median absolute standardized bias drops from 32.7 to 3.05. Overall, matching reduces the bias by about two thirds. Similarly, comparing the pseudo-R^2 of the propensity score estimation before and after matching, we find a significant drop in explanatory power. For instance, for the effect (d, c) versus $(0, 0)$, the pseudo-R^2 before matching is 0.354, i.e. the covariates are relevant predictors in the overall sample. However, on the matched sample of nearest neighbors, the pseudo-R^2 of the same selection regression drops to 0.037, i.e. in the matched sample, there is no remaining systematic difference in observables between treated and control firms. Put differently, our matching procedure does a good job in balancing firm and sector characteristics and to match comparable firms.

Based on these findings, we can turn to estimating the various treatment effects of product and process innovations on firm-level export propensity. Here, we use a radius matching as our reference model outcome. This type of matching requires that the matched control units exhibit a propensity score that exhibits an absolute difference to the treated unit which is not bigger than the chosen radius. Hence, in contrast to other matching estimates such as k-nearest neighbor matching or kernel matching, radius matching enforces a certain matching quality depending on the size of the radius (see Smith and Todd, 2005, for a discussion). We choose a radius of 0.05 in our benchmark model. However, we consider alternative matching estimators and a smaller radius in the sensitivity analysis. The most important findings based on the chosen procedure are summarized in Table 5.

Table 3: PRODUCT AND PROCESS INNOVATIONS: MULTINOMIAL LOGIT

	$(0,c)$	$(d,0)$	(d,c)
	(1)	(2)	(3)
Firm-level variables			
ln(Turnover) in $t-1$	.334	.353	.790
	(.056)	(.040)	(.035)
ln(Turnover per worker) in $t-1$	-.161	-.246	-.552
	(.094)	(.064)	(.056)
Indic.: Lacking own capital	1.313	1.044	1.062
	(.239)	(.184)	(.167)
Indic.: Lacking external capital	-.555	.018	-.333
	(.270)	(.201)	(.186)
Indic.: Long amortization period	1.227	1.555	1.838
	(.188)	(.137)	(.119)
Indic.: Imperfect cooperation poss.	.126	.067	.639
	(.253)	(.183)	(.159)
Sector-level variables			
for Germany			
ln(Value-added) in $t-1$	-.417	.414	.530
	(.250)	(.172)	(.146)
ln(Value-added per worker) in $t-1$	-1.905	-2.044	-1.434
	(.544)	(.369)	(.323)
ln(Unit labor cost) in $t-1$	.050	2.421	2.953
	(.877)	(.622)	(.530)
for EU14			
ln(Value-added) in $t-1$	.626	-.448	-.504
	(.345)	(.225)	(.193)
ln(Value-added per worker) in $t-1$	.549	.200	.187
	(.410)	(.277)	(.247)
ln(Unit labor cost) in $t-1$	.842	-2.603	-2.921
	(.757)	(.539)	(.461)
Constant	-8.514	-11.124	-11.696
	(1.985)	(1.400)	(1.180)
e(N)		4499	

Source: Ifo Innovation Survey, 1994-2004.

Table 4: PRODUCT AND PROCESS INNOVATIONS: BIVARIATE PROBIT

	Product innovation	Process innovation
	(1)	(2)
Firm-level variables		
ln(Turnover) in $t-1$	.352	.346
	(.017)	(.016)
ln(Turnover per worker) in $t-1$	-.258	-.238
	(.028)	(.027)
Indic.: Lacking own capital	.429	.400
	(.079)	(.074)
Indic.: Lacking external capital	-.058	-.223
	(.087)	(.081)
Indic.: Long amortization period	.821	.628
	(.057)	(.052)
Indic.: Imperfect cooperation poss.	.230	.306
	(.073)	(.067)
Sector-level variables		
for Germany		
ln(Value-added) in $t-1$	.326	.114
	(.074)	(.071)
ln(Value-added per worker) in $t-1$	-.640	-.428
	(.161)	(.155)
ln(Unit labor cost) in $t-1$	1.638	.971
	(.269)	(.258)
for EU14		
ln(Value-added) in $t-1$	-.325	-.047
	(.098)	(.093)
ln(Value-added per worker) in $t-1$	-.026	.046
	(.122)	(.120)
ln(Unit labor cost) in $t-1$	-1.762	-.824
	(.232)	(.224)
Constant	-5.810	-4.619
	(.593)	(.566)
at ρ	.899	
	(.034)	
e(N)	4499	

Source: Ifo Innovation Survey, 1994-2004.

Table 5: Multiple treatment effects: Radius matching, $r = 0.05$

T—C	$\hat{\theta}$	$\hat{\sigma}^a_\theta$	$\hat{\sigma}^s_\theta$	$\hat{\alpha}$	$\hat{\sigma}^a_\alpha$	$\hat{\sigma}^s_\alpha$	$\hat{\gamma}$	$\hat{\sigma}^a_\gamma$	$\hat{\sigma}^s_\gamma$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(01) $(d,c) - (0,0)$	.080	.033	.037	.103	.011	.033	.106	.024	.033
(02) $(0,0) - (d,c)$	-.128	.018	.048	-.103	.011	.033	-.106	.024	.033
(03) $(d,c) - (0,c)$	.157	.006	.084	.159	.031	.078	.140	.008	.065
(04) $(0,c) - (d,c)$	-.174	.031	.062	-.159	.031	.078	-.140	.008	.065
(05) $(d,0) - (d,c)$	-.033	.014	.032	-.018	.014	.023	-.031	.000	.037
(06) $(d,c) - (d,0)$	.013	.006	.022	.018	.014	.023	.031	.000	.037
(07) $(0,0) - (d,0)$	-.081	.025	.056	-.081	.016	.047	-.076	.024	.037
(08) $(d,0) - (0,0)$	.083	.025	.043	.081	.016	.047	.076	.024	.037
(09) $(0,0) - (0,c)$	-.017	.040	.079	-.009	.032	.074	.034	.025	.066
(10) $(0,c) - (0,0)$	-.045	.034	.063	.009	.032	.074	-.034	.025	.066
(11) $(0,c) - (d,0)$	-.131	.034	.070	-.124	.029	.067	-.110	.008	.069
(12) $(d,0) - (0,c)$	.121	.038	.073	.124	.029	.067	.110	.008	.069

Source: Ifo Innovation Survey, 1994-2004.
T denotes the treatment, C the control group. Possible treatments are as follows: $(0,0)$ (the *no treatment* case), $(d,0)$ (new product innovations only), $(0,c)$ (new process innovations only), and (d,c) (both new product and new process innovations).

In the table, we report estimates of all three treatment effects, $\theta^{m,l}$, $\alpha^{m,l}$, and $\gamma^{m,l}$ for all treatment pairs m and l and their standard errors. In the first table column, we indicate the treatment (labeled T). For instance, (d, c) refers to firms that got the treatment product and process innovation. The second column identifies the treatment of the comparison group (i.e., that for the matched control units; labeled C) in a similar way. For instance, the first row of results in the table indicates the effect of receiving the treatment (d, c) as compared to the control units with treatment $(0, 0)$. The other columns report the estimates for the various treatment effect concepts ($\hat{\theta}$, $\hat{\alpha}$, $\hat{\gamma}$), the analytical standard errors ($\hat{\sigma}^a_\theta$, $\hat{\sigma}^a_\alpha$, $\hat{\sigma}^a_\gamma$), and their sub-sampling-based counterparts ($\hat{\sigma}^s_\theta$, $\hat{\sigma}^s_\alpha$, $\hat{\sigma}^s_\gamma$).[7] Our results indicate that the analytical standard errors are slightly more conservative (i.e., smaller) than the bootstrapped ones. In the subsequent discussion we will base our inference on bootstrapped rather than analytical standard errors.

Overall, the results indicate that there is a strong, positive role to play for product innovation for a firm's propensity to export. For instance, firms that conduct new product and process innovations (the treated – T in the first table column – receive (d, c)) exhibit a significantly higher export propensity than ones that neither do product nor process innovations (the matched controls – C in the second table column – receive $(0, 0)$). The estimates suggest that firms receiving the treatment (d, c) exhibit an export propensity that is about 8 percentage points higher than for those receiving the treatment $(0, 0)$. Firms receiving the treatment $(0, 0)$ (i.e., no innovation at all) exhibit an export propensity that is about 13 percent lower than for ones with treatment (d, c). While these two ATTs are significantly different from zero at conventional levels, they are not significantly different from each other. The average treatment effect of (actually or hypothetically) receiving the treatment process and product innovation (d, c), given that a firm receives either (d, c) or $(0, 0)$, is $\hat{\alpha} \approx 0.10$. Hence, product and process innovation together enhance a firm's export propensity by about 10 percentage points. Similar conclusions apply for the ATE: product and process innovation together increase a firm's propensity to export by about $\hat{\gamma} \approx 0.11$ – i.e., 11 percentage points –, irrespective of and unconditional on which treatment it actually received.

[7] We rely on the result in Abadie and Imbens (2006) that sub-sampling standard errors provide unbiased estimates of the true ones while bootstrapped standard errors do not. Here, we rely on a 1000 draws of sub-samples of size 3350.

The effect of product innovation is even stronger if a firm already engages in process innovation. This can be seen from a comparison of the point estimates in the third and fourth rows in the table where the treated T receive (d, c) $(0, c)$ and the matched control units C receive $(0, c)$ (d, c). These point estimates are larger in absolute values than those in the first and second lines, irrespective of whether $\hat{\theta}$, $\hat{\alpha}$, or $\hat{\gamma}$ are considered. Even switching from process to product innovation entails significant positive effects on export propensity (consider the two rows at the bottom of Table 5). While product innovations alone raise a firm's propensity to export significantly (see lines 7-8 in the table), their impact is larger if process innovations were already realized. By way of contrast, there is no significant increase in export propensity to be expected if an already product innovating firm undertakes process innovation, in addition. Similarly, process innovations alone exert an insignificant impact on export propensity (see lines 9-10 in the table).

Is there any gain from matching in this data set? To shed light on this issue, we may compare the average treatment effect under the assumption of exogeneity of all regressors, ($\hat{\gamma}_{exog.}$), with its endogenous counterpart as reported in Table 5 ($\hat{\gamma}$). The exogenous treatment effect may be thought of as the simple comparison of the average export propensity among the treated and the untreated firms for each treatment. The corresponding exogenous treatment effect estimates (i.e., the simple mean comparisons) together with their endogenous treatment effect counterparts as of Table 5 are summarized in Table 6. Since the average treatment effects are symmetric throughout, we only report every second estimate as compared to Table 5.

It seems worth noting that in one of the experiments even the sign of the exogenous treatment effect point estimate differs from the endogenous one (treatment $(0, c) - -(d, 0)$). Moreover, for five of the six parameters the (absolute) difference in the point estimates is higher than 50 percent of the endogenous treatment effect parameter. In many of these cases this difference is significant. Hence, accounting for self-selection into treatment is important in this data set, leading to significantly different average treatment effect estimates.

Table 6: EXOGENOUS VERSUS ENDOGENOUS MULTIPLE TREATMENT EFFECTS

T—C	$\hat{\gamma}_{exog.}$	$\hat{\sigma}^s_{\gamma_{exog.}}$	$\hat{\gamma}$	$\hat{\sigma}^s_{\gamma}$
	(1)	(2)	(3)	(4)
(01) $(d,c)-(0,0)$	.233	.018	.106	.033
(03) $(d,c)-(0,c)$	.091	.020	.140	.065
(06) $(d,c)-(d,0)$	.014	.017	.031	.037
(08) $(d,0)-(0,0)$	.142	.030	.076	.037
(10) $(0,c)-(0,0)$	-.027	.047	-.034	.066
(11) $(0,c)-(d,0)$	.169	.045	-.110	.069

Source: Ifo Innovation Survey, 1994-2004.
T denotes the treatment, C the control group. Possible treatments are as follows: $(0,0)$ (the *no treatment* case), $(d,0)$ (new product innovations only), $(0,c)$ (new process innovations only), and (d,c) (both new product and new process innovations). The endogenous treatment effects are repeated from Table 5.

6 Sensitivity analysis and discussion

We undertake several robustness checks to assess the sensitivity of our findings. In these experiments, we only report re-sampling-based standard errors of the endogenous treatment effect estimates for the sake of brevity. First, we consider an alternative radius of only 0.005 instead of 0.05. Hence, we enforce a considerably higher precision of the matching estimates there than we did in our benchmark model in Table 5. The results are summarized in Table 7. Overall, we may conclude that changing the radius does not affect our conclusions from above, neither in qualitative nor in quantitative terms.

Second, we use a nearest neighbor matching estimator in Table 8, where we compare each treated firm's outcome to a single nearest neighbor, irrespective of the difference of the best match's difference in propensity score to the treated unit (i.e., the difference might be smaller or larger than than 5 or 0.05 percentage points as required with the previous radius matching estimates). In general, it turns out that the nearest-neighbor-matching-based estimates are quite close to the original ones both in qualitative and in quantitative terms.

Table 7: MULTIPLE TREATMENT EFFECTS: RADIUS MATCHING, $r = 0.005$

T—C	$\hat{\theta}$	$\hat{\sigma}^s_\theta$	$\hat{\alpha}$	$\hat{\sigma}^s_\alpha$	$\hat{\gamma}$	$\hat{\sigma}^s_\gamma$
	(1)	(2)	(3)	(4)	(5)	(6)
(01) $(d,c)-(0,0)$	.077	.039	.103	.038	.105	.036
(02) $(0,0)-(d,c)$	-.131	.051	-.103	.038	-.105	.036
(03) $(d,c)-(0,c)$	.178	.092	.177	.086	.156	.070
(04) $(0,c)-(d,c)$	-.170	.068	-.177	.086	-.156	.070
(05) $(d,0)-(d,c)$	-.034	.035	-.020	.028	-.042	.041
(06) $(d,c)-(d,0)$	.015	.028	.020	.028	.042	.041
(07) $(0,0)-(d,0)$	-.058	.065	-.063	.056	-.063	.042
(08) $(d,0)-(0,0)$	.075	.052	.063	.056	.063	.042
(09) $(0,0)-(0,c)$	-.013	.093	-.006	.088	.051	.074
(10) $(0,c)-(0,0)$	-.045	.075	.006	.088	-.051	.074
(11) $(0,c)-(d,0)$	-.111	.080	-.141	.080	-.114	.075
(12) $(d,0)-(0,c)$	.152	.087	.141	.080	.114	.075

Source: Ifo Innovation Survey, 1994-2004.
T denotes the treatment, C the control group. Possible treatments are as follows: $(0,0)$ (the *no treatment* case), $(d,0)$ (new product innovations only), $(0,c)$ (new process innovations only), and (d,c) (both new product and new process innovations).

Third, we use an Epanechnikov kernel-based matching with a bandwidth of 0.06 instead of the original radius matching in Table 9. This kernel estimator is potentially more efficient than the radius matching estimator but it gives some weight to less comparable units than radius matching with a narrow radius does. The bandwidth determines this trade-off between efficiency and unbiasedness. Let us refer to a control unit's absolute difference to a treated firm's propensity score as Δ. Then, only those firms with $\Delta \leq 0.06$ are given a weight of $1-(\Delta/0.06)^2$ and zero else. Hence, a larger bandwidth covers more observations and gives more weight to less comparable ones. However, as Table 9 indicates, the choice of an Epanechnikov kernel estimator leads to conclusions that are virtually identical to the original ones.

Fourth, we infer to which extent our last statement about kernel matching depends on the choice of the bandwidth in Table 10. For this we choose a

Table 8: Multiple treatment effects: Nearest neighbor matching

T—C	$\hat{\theta}$	$\hat{\sigma}^s_\theta$	$\hat{\alpha}$	$\hat{\sigma}^s_\alpha$	$\hat{\gamma}$	$\hat{\sigma}^s_\gamma$
	(1)	(2)	(3)	(4)	(5)	(6)
(01) $(d, c) - (0, 0)$	.085	.047	.105	.044	.102	.041
(02) $(0, 0) - (d, c)$	-.127	.066	-.105	.044	-.102	.041
(03) $(d, c) - (0, c)$	.148	.126	.145	.115	.126	.085
(04) $(0, c) - (d, c)$	-.129	.082	-.145	.115	-.126	.085
(05) $(d, 0) - (d, c)$	-.037	.047	-.025	.030	-.049	.048
(06) $(d, c) - (d, 0)$	.021	.030	.025	.030	.049	.048
(07) $(0, 0) - (d, 0)$	-.042	.079	-.050	.064	-.054	.048
(08) $(d, 0) - (0, 0)$	.070	.060	.050	.064	.054	.048
(09) $(0, 0) - (0, c)$	-.060	.109	-.043	.099	.023	.085
(10) $(0, c) - (0, 0)$	-.076	.090	.043	.099	-.023	.085
(11) $(0, c) - (d, 0)$	-.084	.092	-.152	.082	-.077	.088
(12) $(d, 0) - (0, c)$	.178	.097	.152	.082	.077	.088

Source: Ifo Innovation Survey, 1994-2004.
T denotes the treatment, C the control group. Possible treatments are as follows: $(0, 0)$ (the *no treatment* case), $(d, 0)$ (new product innovations only), $(0, c)$ (new process innovations only), and (d, c) (both new product and new process innovations).

much narrower bandwidth of 0.02 which mimics but is not identical to) the choice of a smaller radius under radius matching. Hence, it is not surprising that we come up with insights that are fairly close to the previous ones, pointing to the robustness of our original findings.

Finally, we use an alternative kernel, namely a Gaussian one with a bandwidth of 0.06 (see Table 11). There, the kernel weight is $\phi(\Delta/0.06)$, where $\phi(\cdot)$ is the normal density and Δ is the absolute difference in propensity scores between a treated and a control unit. However, as Table 11 indicates, the original conclusions are also robust to the choice of an alternative matching estimator.

Table 9: Multiple treatment effects: Kernel matching, Epanechnikov kernel, bandwidth 0.06

T—C	$\hat{\theta}$	$\hat{\sigma}^s_\theta$	$\hat{\alpha}$	$\hat{\sigma}^s_\alpha$	$\hat{\gamma}$	$\hat{\sigma}^s_\gamma$
	(1)	(2)	(3)	(4)	(5)	(6)
(01) $(d,c)-(0,0)$	.079	.037	.102	.033	.105	.033
(02) $(0,0)-(d,c)$	-.128	.048	-.102	.033	-.105	.033
(03) $(d,c)-(0,c)$	.165	.087	.166	.080	.142	.066
(04) $(0,c)-(d,c)$	-.174	.062	-.166	.080	-.142	.066
(05) $(d,0)-(d,c)$	-.030	.032	-.017	.023	-.030	.038
(06) $(d,c)-(d,0)$	.012	.022	.017	.023	.030	.038
(07) $(0,0)-(d,0)$	-.079	.056	-.080	.047	-.075	.037
(08) $(d,0)-(0,0)$	.082	.043	.080	.047	.075	.037
(09) $(0,0)-(0,c)$	-.018	.080	-.011	.075	.037	.067
(10) $(0,c)-(0,0)$	-.044	.064	.011	.075	-.037	.067
(11) $(0,c)-(d,0)$	-.130	.070	-.125	.068	-.112	.070
(12) $(d,0)-(0,c)$	.123	.075	.125	.068	.112	.070

Source: Ifo Innovation Survey, 1994-2004.
T denotes the treatment, C the control group. Possible treatments are as follows: $(0,0)$ (the *no treatment* case), $(d,0)$ (new product innovations only), $(0,c)$ (new process innovations only), and (d,c) (both new product and new process innovations).

Overall, neither the functional form of the multiple choice model, nor the alternative values for the radius, the type of the matching estimator (radius versus nearest-neighbor versus kernel), nor the kernel bandwidths or the functional forms of the kernels have a qualitative impact on the significant findings in the original table.

In general, this paper's analysis provides evidence that product innovation is more important than process innovation for a firm's export propensity. However, while process innovation seems of little relevance for export propensity, it improves a firm's probability to export if it is accompanied by product innovation.

Table 10: MULTIPLE TREATMENT EFFECTS: KERNEL MATCHING, EPANECHNIKOV KERNEL, BANDWIDTH 0.02

T—C	$\hat{\theta}$ (1)	$\hat{\sigma}^s_{\theta}$ (2)	$\hat{\alpha}$ (3)	$\hat{\sigma}^s_{\alpha}$ (4)	$\hat{\gamma}$ (5)	$\hat{\sigma}^s_{\gamma}$ (6)
(01) $(d,c)-(0,0)$	.073	.039	.100	.037	.103	.036
(02) $(0,0)-(d,c)$	-.129	.054	-.100	.037	-.103	.036
(03) $(d,c)-(0,c)$	.205	.111	.201	.101	.164	.076
(04) $(0,c)-(d,c)$	-.170	.065	-.201	.101	-.164	.076
(05) $(d,0)-(d,c)$	-.032	.035	-.017	.026	-.036	.042
(06) $(d,c)-(d,0)$	.012	.025	.017	.026	.036	.042
(07) $(0,0)-(d,0)$	-.067	.065	-.070	.054	-.067	.042
(08) $(d,0)-(0,0)$	.080	.049	.070	.054	.067	.042
(09) $(0,0)-(0,c)$	-.012	.092	-.006	.086	.061	.076
(10) $(0,c)-(0,0)$	-.038	.068	.006	.086	-.061	.076
(11) $(0,c)-(d,0)$	-.125	.075	-.131	.073	-.128	.080
(12) $(d,0)-(0,c)$	.134	.080	.131	.073	.128	.080

Source: Ifo Innovation Survey, 1994-2004.
T denotes the treatment, C the control group. Possible treatments are as follows: $(0,0)$ (the *no treatment* case), $(d,0)$ (new product innovations only), $(0,c)$ (new process innovations only), and (d,c) (both new product and new process innovations).

7 Conclusions

Our goal in this paper was to provide novel empirical insights in the role of product versus process innovation on export propensity at the firm level. Either of these modes of innovation has been hypothesized to affect firm-level productivity in previous theoretical work. A smaller body of theoretical research even pointed to the differential impact of these two types of innovation on a firm's export propensity. We aim at assessing the latter relationship empirically. Economic theory suggests that firms do not undertake innovations at random, neither product nor process innovations. Hence, empirical work should pay attention to the likely self-selection of firms into innovations. Viewing innovations as a 'treatment', this lends support to an endogenous treatment approach to innovations and export propensity. With two modes

Table 11: MULTIPLE TREATMENT EFFECTS: KERNEL MATCHING, GAUSSIAN KERNEL

T—C	$\hat{\theta}$	$\hat{\sigma}^s_{\theta}$	$\hat{\alpha}$	$\hat{\sigma}^s_{\alpha}$	$\hat{\gamma}$	$\hat{\sigma}^s_{\gamma}$
	(1)	(2)	(3)	(4)	(5)	(6)
(01) $(d,c)-(0,0)$	.075	.037	.101	.035	.104	.035
(02) $(0,0)-(d,c)$	-.129	.051	-.101	.035	-.104	.035
(03) $(d,c)-(0,c)$	.185	.098	.184	.091	.151	.072
(04) $(0,c)-(d,c)$	-.172	.064	-.184	.091	-.151	.072
(05) $(d,0)-(d,c)$	-.030	.035	-.017	.025	-.032	.040
(06) $(d,c)-(d,0)$	.012	.024	.017	.025	.032	.040
(07) $(0,0)-(d,0)$	-.075	.059	-.076	.050	-.072	.039
(08) $(d,0)-(0,0)$	.081	.045	.076	.050	.072	.039
(09) $(0,0)-(0,c)$	-.020	.077	-.012	.073	.047	.072
(10) $(0,c)-(0,0)$	-.041	.069	.012	.073	-.047	.072
(11) $(0,c)-(d,0)$	-.129	.075	-.126	.073	-.119	.074
(12) $(d,0)-(0,c)$	.125	.082	.126	.073	.119	.074

Source: Ifo Innovation Survey, 1994-2004.
T denotes the treatment, C the control group. Possible treatments are as follows: $(0,0)$ (the *no treatment* case), $(d,0)$ (new product innovations only), $(0,c)$ (new process innovations only), and (d,c) (both new product and new process innovations).

of innovations – product and process innovations –, one is then faced with an econometric framework with multiple endogenous treatments.

Adopting a so-called matching approach based on the propensity score and using survey data of German firms available from the Ifo Institute, we find that there is significant bias of the impact of product and process innovations on export propensity when ignoring self-selection into either mode of innovation. This bias was quite substantial in our application, having been particularly large for firms with only product or process innovations as compared to ones that did not innovate. The largest estimated self-selection bias in the data amounted to more than 200 percent, depending on the mode of innovations (product and/or process innovation).

Overall, the results point to the importance of product innovation relative to process innovation. In comparison, there is no evidence that process innovation fosters a firm's propensity to export beyond product innovation. This can be viewed as evidence on the importance of the extensive margin in product space for a firm's entry into export markets.

Angrist, J.D. (1998), Estimating Labor Market Impact of Voluntary Military Service Using Social Security Data, *Econometrica* **66**, 249-288.

Baily, M.N. and H. Gersbach (1995), Efficiency in Manufacturing and the Need for Global Competition, *Brookings Papers on Economic Activity: Microeconomics*, 307-58.

Basile, R. (2001), Export Behavior of Italian Manufacturing Firms Over the Nineties: The Role of Innovation, *Research Policy* **30**, 1185-1201.

Bernard, A. and J.B. Jensen (1999), Exceptional Export Performance: Cause, Effect, or Both?, *Journal of International Economics* **47**, 1-25.

Braunerhjelm, P. (1996), The Relation Between Firm Specific Intangibles and Exports, *Economic Letters* **53**, 21319.

Cassiman, B. and Martínez-Ros (2004), Innovation and Exports: Evidence from Spanish Manufacturing, unpublished manuscript, IESE Business School.

Cohen, W.M. and S. Klepper (1996), Firm Size and the Nature of Innovation within Industries: The Case of Process and Product R&D, University of Zurich, *Review of Economics and Statistics* **78**, 232-243.

Davidson and MacKinnon (2004), *Econometric Theory and Methods*, Oxford University Press, New York.

Dahejia, R.H. and S. Wahba (1999), Causal Effects in Non-Experimental Studies: Reevaluating the Evaluation of Training Programmes, *Journal of the American Statistical Association* **94**, 1053-1062.

Dehejia, R. H. and S. Wahba (2002), Propensity score matching methods for non-experimental causal studies. *Review of Economics and Statistics* **84(1)**, 151-161.

Foellmi, R. and J. Zweimller (2005), Mass Consumption, Exclusion, and Technological Unemployment, unpublished manuscript, University of Zurich.

Frölich, M. (2004), Programme Evaluation with Multiple Treatments, *Journal of Economic Surveys* **18**, 181-224.

Grossman, G.M. and E. Helpman (1989), Product Development and International Trade, *Journal of Political Economy* **97**, 1261-83.

Grossman, G.M. and E. Helpman (1990), Comparative Advantage and Long-run Growth, *American Economic Review* **80**, 796-815.

Heckman, J.J., H. Ichimura, and P. Todd (1997), Matching as an Econometric Evaluation Estimator: Evidence from a Job Training Programme, *Review of Economic Studies* **64**, 605-654.

Heckman, J.J., H. Ichimura, and P. Todd (1998), Matching as an Econometric Evaluation Estimator, *Review of Economic Studies* **65**, 261-294.

Heckman, J.J., R.J. LaLonde, and J.A. Smith (1999), The Economics and Econometrics of Active Labor Market Programs, in O. Ashenfelter and D. Card (eds.), *Handbook of Labor Economics*, Vol. III, 1865-2073.

Hirsch, S. and I. Bijaoui (1985), R&D Intensity and Export Performance: A Micro View, *Weltwirtschaftliches Archiv* **121**, 138-51.

Hughes, K.S. (1986), Exports and Innovation, *European Economic Review* **30**, 383-99.

Imbens, G. (2000), *Biometrika.* **87(3)**, 706-710.

Jensen, R. and M. Thursby (1987), A Decision Theoretic Model of Innovation, Technology Transfer, and Trade, *Review of Economic Studies* **54**, 631-47.

Kumar, N. and N.S. Siddharthan (1994), Technology, Firm Size and Export Behavior in Developing Countries: The Case of Indian Enterprise, *Journal of Development Studies* **32**, 288-309.

Lachenmaier, S. and L. W¨ßmann (2005), Does Innovation Cause Exports? Evidence from Exogenous Innovation Impulses and Obstacles Using German Micro Data, *Oxford Economic Papers* **??**, 1-34.

Smith, J.A. and P.E. Todd (2005), Does Matching Overcome Lalonde's Critique of Nonexperimental Estimators, *Journal of Econometrics* **125**, 305-353.

Leamer, E.E. and J. Levinsohn (1995), International Trade Theory: The Evidence, in: G.M. Grossman and K. Rogoff (eds.), *The Handbook of International Economics, vol. III*, Elsevier, 1339-1394.

Lechner, M. (2001), Identification and Estimation of Causal Effects of Multiple Treatments Under the Conditional Independence Assumption, in: M. Lechner and F. Pfeiffer (eds.), *Econometric Evaluation of Labor Market Policies*, ZEW Economic Studies, vol. 13, 43-58.

Lee, M.-J. (2005), *Micro-Econometrics for Policy, Program and Treatment Effects*, Oxford: Oxford University Press.

Martin, S. (1983), Endogenous Firm Efficiency in a Cournot Principal-Agent Model, *RAND Journal of Economics* **59**, 445-50.

Roper, S. and J.H. Love (2002), Innovation and Export Performance: Evidence from the UK and German Manufacturing Plants, *Research Policy* **31**, 1087-1102.

Rosenbaum, P. R. and D. B. Rubin (1985), Constructing a Control Group Using Multivariate Matched Sampling Methods That Incorporate the Propensity Score, *The American Statistician* **39(1)**, 33-38.

Segerstrom, P.S., T.C.A. Anant, and E. Dinopoulos (1990), A Schumpeterian Model of the Product Life Cycle, *American Economic Review* **80**, 1077-91.

Wakelin, K. (1998), Innovation and Export Behaviour at the Firm Level, *Research Policy* **26**, 829-41.

Wooldridge, J.M. (2002), *Econometric Analysis of Cross-section and Panel Data*, Cambridge, MA: MIT Press.