Empir Econ (2013) 44:329–354
DOI 10.1007/s00181-009-0322-6

Endogenous product versus process innovation and a firm's propensity to export

Sascha O. Becker · Peter H. Egger

Received: 16 April 2008 / Accepted: 6 August 2009 / Published online: 18 November 2009

Abstract This article 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 destruction 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 of launching new innovations and their impact on export propensity at the firm level through a double treatment approach.

Keywords Product innovation · Process innovation · Propensity to export · Multiple treatment effects estimation

JEL Classification F1 · O3 · L1

Electronic supplementary material The online version of this article (doi:10.1007/s00181-009-0322-6) contains supplementary material, which is available to authorized users.

S. O. Becker (✉)
Stirling Management School, University of Stirling, Stirling, FK9 4LA, UK
e-mail: sascha.becker@stir.ac.uk

P. H. Egger
KOF, ETH Zurich, Weinbergstrasse 35, 8092 Zurich, Switzerland

1 Introduction

Research on the role of innovation on economic outcomes has for long been at the heart of three different fields of the profession: macro-economics, international economics, and industrial economics. Two central assumptions can be thought of unifying these literatures, namely that innovation is endogenous at the firm-level, and it is undertaken for the sake of distinguishing products from competitors (horizontally or qualitatively), thereby securing a firm's market position against its rivals. We may associate innovation of that kind with what we will refer to as *product innovation*. While macro and international economics tend to treat firm-level productivity as being exogenous, there is a well-established literature in industrial organization, which suggests that endogenous productivity gains are possible through *process innovation*.

Overall, product characteristics and high productivity are now understood as the corner stones for firms to sustain competition in domestic but even more so in global markets. Accordingly, we hypothesize that there is a distinct role to play for product and process innovations. Yet, their differential impact on domestic and foreign market penetration is hitherto the target of only small bodies of theoretical and empirical study. To a large extent, product and/or process characteristics and the corresponding modes of innovation are modeled as lying beyond a firm's choice. The latter is, however, largely at odds with both economic intuition and stylized facts.

Our contribution is to explicitly take into account the endogeneity of product and process innovations when estimating their impact on exports. We do so with the use of linked data from two unique firm surveys that include information on the determinants of innovations as well as on the business environment in which the firms operate. In contrast to earlier study, we use more than a decade of data, and we employ 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. We address dynamics by controlling for past values of innovations, expenditures.

The main findings from a panel data set of German firms can be summarized in the following way. First, pursuit of both process and product innovations leads to a higher probability to export than in the absence of any kind of innovation. However, our results point to a dominant importance of product innovation relative to process innovation for the decision to export. When done alone, product innovation is more important for firm-level export behavior than is process innovation. Process innovations increase a firm's probability to export only when being combined with product innovations. However, process innovations marginally raise a firm's export-to-sales ratio at the intensive margin of exports.

The remainder of this article is organized as follows. The next section provides an overview of earlier theoretical and empirical study 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 Sect. 5, which are discussed and their sensitivity is investigated in Sect. 6, and the last section concludes with a summary of the central findings.

2 Previous research and the contribution of this article

2.1 Economic theory on innovation

There is a sizeable body of theoretical study 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 for economic growth in a world where consumers have a taste for variety and/or a high quality of available products (see Grossman and Helpman 1991, Chaps. 3 and 4). Only recently, macro-economists have explored the potential differences between product and process innovations for income, focusing on heterogeneous agents and technological unemployment (Foellmi and Zweimüller 2006).

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, Chaps. 9–11; Segerstrom et al. 1990). A key hypothesis in this literature is that of innovation-driven exports. In recent dynamic models with firms that exhibit heterogeneous productivity levels and, hence, heterogeneous marginal production costs (Jovanovic 1982; Hopenhayn 1992; Melitz 2003; Grossman et al. 2006), investment in firm-specific assets has led to a selection of firms: the least productive ones do not participate in 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. In this context, investment in firm-specific assets (which one could associate with product innovation; see Spence 1984) and 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. Subsequent research established insights in the relationship between process innovation and competitive pressure at the local (Martin 1993) and the global level (Baily and Gersbach 1995). Boone (2000) explicitly deals with product versus process innovations and their relation with competitive pressure. When assuming that the aggregate efficiency can be measured by the (inverse of) average production costs, his 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 may 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. Recently, Atkeson and Burstein (2007) and Constantini and Melitz (2008) have analyzed dynamic industry models to formalize linkages between firm-level productivity and the choices of both to export and to invest in R&D or adopt new technology. In these models, productivity distinguishes heterogeneous firms, and its evolution is endogenous and affected by innovation decisions at the firm level (apart from a stochastic component).

A common feature of many of the above models is that product and process innovations are endogenous, a feature that we will explicitly deal with in our empirical analysis.

2.2 Empirical work on the determinants and effects of innovation

Numerous previous empirical studies point to a positive impact of innovation as such 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 (Wakelin 1998; Bernard and Jensen 1999; Roper and Love 2002; Lachenmaier and Wößmann 2006; Cassiman and Martínez-Ros 2007). Overall, these studies find a strong positive impact of innovations on exports.[1] While most of the above 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 2007).

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 1986), empirical microeconometric study on innovation-driven exports tends to model the selection of firms into innovations as a random (exogenous) process.

However, there is a large evidence on a systematic determination of innovation. We argue that the processes determining exporting and innovation—in particular, product and process innovations—are correlated. Unless one aims at conditioning on a suitable set of determinants of innovations, it may be impossible to estimate the causal effect of innovations on exports.

Previous study on the determinants of innovations found that, among other things, larger, exporting firms are more inclined toward innovating, that innovations display a persistent pattern, and that specific obstacles to innovations matter. Let us briefly survey some of the previous study on the determinants of innovations before turning to empirical studies on the consequences of innovations.[2]

Cohen and Klepper (1996) formulate and test a 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.

[1] A smaller number of studies that employed the less preferable R&D expenditures as an indirect measure of innovations failed to find such a positive impact (see Cassiman and Martínez-Ros 2007, for a survey).

[2] Notice that space constraints dictate an eclectic approach here. Accordingly, we will primarily discuss research which relates to our study with regard to the data used (based on survey data which are collected by Ifo or other institutions in Germany), the methodology chosen, or the hypotheses generated.

Flaig and Stadler (1994) and Peters (2007), based on dynamic panel data models to understand innovation activities, show that innovations have a persistent component, which is why we control for past innovation expenditures in some of our specifications.

As to the consequences of innovations at the level of the firm, most of the research focuses on employment (see Smolny 1998, who also considers effects of innovations on prices, output, and sales; Smolny and Schneeweis 1999; Lachenmaier and Rottmann 2007). There is less empirical study on the question as to what extent innovations drive exports.

Early studies (e.g., Hirsch and Bijaoui 1985, and Schlegelmilch and Crook 1988) looking into the effects of innovations on exports used measures of innovation input and arrived at mixed conclusions (see Ebling and Janz 1999, for an overview).

Firm-level studies which used more direct measures of innovation output (i.e., actual innovations) are those of Wagner (1996) and Wakelin (1997, 1998). Wagner uses a sample of firms in the German State of Lower Saxony and finds a positive impact of new products introduced on exports. Wakelin employs British data and reports a positive impact of innovating on the intensive and extensive margins of exports at the firm level. However, these mentioned studies have treated innovations as exogenous.

A first example of research on the impact of endogenous innovations on exports is the one by Entorf et al. (1988), based on data from the Ifo Innovation Survey. They estimate a simultaneous equation system of exports, innovation, and labor demand and identify not only a positive impact of innovations (captured by an indicator variable) on exports but also one of exports on innovations. Ebling and Janz (1999) study the impact of innovations (captured by a binary variable) on the extensive margin of exports in the service sector, using data for 1997 from the Mannheim Innovation Panel. Their results are based on a two-step probit model and simultaneous probit models and point to a positive impact of innovations on exports, but not vice versa.

The study most closely related to ours is that of Lachenmaier and Wößmann (2006). They apply instrumental-variables procedures to estimate the impact of potentially endogenous innovations on exports at the firm level. They utilize data on 981 firms for the year 2002 and determine innovations by means of linear probability models in a first stage. In contrast to most of the other research on innovations, they employ a set of indicator variables capturing impediments to innovations, which are based on answers of firms to questions in ifo's Innovation Survey. These indicator variables capture the following variables related to reasons for why innovations have or have not been undertaken: the importance of production and resource management, the relevance of an employee suggestion scheme, the lack of necessity to innovate, the lack of equity capital, and the lack of high enough expected returns to innovations as compared to the necessary expenses. In broad terms, they find that such impediments to innovations matter and that such variables can be used as identifying instruments for innovations. Their results indicate that treating innovations as exogenous may lead to largely downward-biased estimates of the impact of innovations on firm-level exports. Our study differs from that of Lachenmaier and Wößmann in several respects. Their focus is on total innovations, and they look into product versus process innovations only in one of their specifications. Furthermore, they use only one cross section of data whereas we employ data from more than a decade of data. Our matching approach includes both contemporaneous as well as lagged variables to capture firms' selection into innovations. Finally, we enrich the Ifo Innovation Survey with further important variables from the ifo Business Survey, which reflect the business environment in which firms take their innovation decisions. In contrast to earlier study in general, 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]

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). The assumption underlying matching is that the observable variables that enter the selection equation(s) capture the deterministic components of that selection process. However, the world is not perfectly deterministic; hence, two firms with the same observable characteristics may ultimately choose to act differently. In order to fix ideas, the board meetings of two "identical firms" might vote differently on the basis of the same evidence; one in favor of innovation, and the other not.

One strategy of exploiting this assumption for the purpose of treatment effect identification is propensity score matching (see Dehejia and Wahba 1999, 2002; Heckman et al. 1997, 1998; Lechner 2001; Heckman et al. 1999, provide a survey).[4]

Since our data set allows us to disentangle whether firms have adopted product innovation versus process innovations—hence, there are two treatment indicators at the firm level (there is no information on the extent of innovations)—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 cannot 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

[3] Recent related studies on endogenous innovation and exports based on non-German data mostly employ innovation input. For instance, Aw et al. (2009) use a short panel data set of British firms in three manufacturing sectors and find evidence of an impact of R&D—i.e., of innovation input—on productivity and, in turn, on exporting. More generally, Bernard and Jensen (1997); Aw et al. (2007); Iacovone and Javorcik (2007), and Lileeva and Trefler (2007), among others, document that exporting is correlated with R&D or adoption of new technology at the firm level. In that context, the article by Aw et al. (2009) indicates that a main channel of influence is the one which runs from past productivity to innovations and, in turn, to exports.

[4] Conditional mean-independence is also assumed in parametric and non-parametric regression methods for inference of average treatment effects. Examples are switching regression models or regression discontinuity design. Alternative to methods which estimate treatment effects under the assumption of conditional mean-independence, econometric theory offers instrumental variables methods. Wooldridge (2002) provides an excellent discussion of the alternative sets of assumptions adopted in the two strands of the literature—based on conditional mean-independence versus instrumental variables estimation. While instrumental variables estimation rests on weaker assumptions than, for instance, propensity score matching in many regards, it adopts stronger assumptions about the stochastic terms in the model (see Wooldridge 2002, pp. 621 and 623). In practice, results are often similar among switching regression, regression discontinuity design, propensity score matching, and instrumental variable estimation if the same observables are used to determine selection.

mutually exclusive 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).[5] A matching approach with multiple treatments has been derived by Lechner (2001).[6]

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 2001). 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 probit model or by a multinomial logit 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 $E\{E[Y^m|\hat{P}^m(\mathbf{x})S = m]|S \neq m\}$ 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 radius matching (each treated firm is compared to all the firms within a certain radius around its propensity score), nearest-neighbor matching (each treated firm is compared to a single control unit), 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,[7] with weights that depend negatively upon the difference in the propensity scores between treated and untreated units). The average treatment effect (i.e., the outer expectation above)

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

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

[7] We employ both an Epanechnikov kernel with two alternative bandwidths (0.06 and 0.02) and a Gaussian kernel to probe the robustness of our results.

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 proposed in Lechner (2001). In empirical applications, these analytic standard errors may deviate considerably from their small-sample counterparts. Therefore, we alternatively compute sub-sampling-based standard errors following Politis et al. (1999). As shown by Abadie and Imbens (2008), these give reliable variance estimates of treatment effects even in small samples. Especially, in our case, sub-sampling may account for the block structure of residuals since firms are repeatedly observed over time. Therefore, inspired by study on block bootstrap estimation (e.g., Fitzenberger 1998) for part of the estimates, we pursue block-sub-sampling by sampling the entire observation vector for each firm instead of simple sub-sampling and assuming that all observations are independently distributed.

4 Data

Our firm-level data are based on two surveys conducted by the Ifo Institute of Economic Research in Munich: the Innovation Survey that is conducted annually, covering more than 1,000 firms in Germany per year; and the Business Survey which is conducted monthly, covering more than 3,000 firms.[8] The Innovation 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. The Business Survey asks about the currently realized and expected situations with regard to business, orders, and demand, etc. The primary aim of that survey is the construction of the Ifo Business Indicator (“Ifo Geschäftsklimaindex”). We were able to merge the data from the two surveys since Ifo made efforts to standardize the link between the alternative surveys which have been conducted quite independently in the recent past. Beyond that, there is an industry indicator that allows us to link industry characteristics at the 2-digit NACE classification level 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 previous six months or not. The corresponding questions that we rely on in our analysis can be translated as follows:

[8] Both data sets can be accessed for scientific use. The access procedure to the ifo *DataPool* is described in more detail in Becker and Wohlrabe (2008)

- *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.[9]
- *In year t we have introduced (or started but not yet completed) new product innovations. In year t we have introduced (or started but not yet completed) new process innovations.*[10] 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 otherwise, and the other is constructed in the same way but for process innovations.

Overall, there are 1,212 firms and 3,401 observations in our database. Note that every observation covers 3 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, 78.01% 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, 61.51% of the firms innovate (i.e., they receive treatments $(d, 0)$, $(0, c)$, or (d, c)). Of these, 23.47% conduct product innovations only $(d, 0)$, 8.84% conduct process innovations only $(0, c)$, and 67.69% 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. These variables may be seen as crucial *supply-side determinants* of innovation inputs. Of these, 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

[9] In the sensitivity analysis reported later, we alternatively use information on the *intensive margin* of exports defined as the share of exports in turnover (rather than only on the decision of whether to export at all or not). The respective question for the extent of exports as a fraction of sales is: *The share of exports in total sales of the respective production unit (in year t) amounted to....*"

[10] In general, the survey is consistent with definitions of innovations used in, e.g., the Oslo Manual issued by the Organization for Economic Co-operation and Development (with a focus on technological product and process innovations; see Sect. 4.2.1 of the manual) or the Community Innovation Survey conducted by the EU member states. The focus on innovations entailing new *technological* improvements of products or processes rules out minor innovations which lead to a change in perception at markets only. The questionnaire details the meaning of product and process innovations as follows: *product innovations* are targeted toward products with a different purpose and/or are technologically sufficiently different from existing ones; *process innovations* encompass modernization and renewal of the production process rather than changes of the product itself and also the introduction of information technology in office and administration. Alternatively, in the sensitivity analysis, we use only completed innovations (excluding innovations that have been started but were not completed in the year of interest). The respective question for completed innovations reads: *In year t, we have introduced (completed) new product innovations. In year t, we have introduced (completed) new process innovations.*

Table 1 Exports and innovations: a summary

Treatment	Export		Total
	0	1	
(0, 0)	477	832	1,309
	36.44	63.56	100.00
(0, c)	71	114	185
	38.38	61.62	100.00
(d, 0)	79	412	491
	16.09	83.91	100.00
(d, c)	121	1,295	1,416
	8.55	91.45	100.00
Total	748	2,653	3,401
	21.99	78.01	100.00

Source: Ifo Innovation Survey, 1994–2004
Possible treatments are as follows: (0, 0) the *no innovation* case, (d, 0) new product innovations only, (0, c) new process innovations only, and (d, c) both new product and new process innovations

3 and 4 as one and 1 and 2 as zero. The use of such impediments as determinants of innovation has been suggested by Lachenmaier and Wößmann (2006).

Furthermore, we include lagged logarithms of sales and sales per employee in our specifications (see Flaig and Stadler 1994, for a motivation of firm size as a determinant of innovations, and Aw et al. 2009, for the relevance of past productivity for innovations. In addition, we control for once-lagged as well as twice-lagged exports at the firm level as two separate regressors (again, Aw et al. 2009, suggest that export status in the past may influence future exports through its impact on innovations and productivity). Moreover, we account for variables capturing the average state of business, orders, and demand and its variance within a year prior to possible innovation events as possible determinants (see Flaig and Stadler 1994, for an early example of using, for instance, demand volatility as a determinant of product and process innovations).

Rather than employing only the main effects of innovation impediments and other firm-level characteristics, we include a large number of interactive terms. For instance, we use a comprehensive set of interactions between firm sales and sales per employee with innovation impediments as well as the state of business, orders, and demand variables.[11]

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 the once-lagged German real value added in nominal Euros (to capture the size of an industry), real value added per worker (to capture industry productivity), and unit labor costs (to capture wage costs per unit of output). Furthermore, we use inverse-distance-weighted values of these variables for the EU14 economies (excluding Germany), where each industry-level explanatory variable, x_{ijt} for industry i and time t, is weighted across the 14 EU member countries as of 1995 excluding Germany

[11] The use of interactions among the state of business, orders, and demand variables is not possible for reasons of multicollinearity.

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.[12]

The industry-level variables control for both a firm's competitive pressure at the domestic and the Western European foreign markets (see Flaig and Stadler 1994; and Peters 2007, for models including industry-level determinants). For instance, the inverse-distance-weighted value addition 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. In contrast, the higher the weighted foreign wage costs relative to foreign output, the lower we expect the competitive pressure for German producers to be ceteris paribus. Hence, the industry-level variables represent *demand-side determinants* of innovation inputs.

Beyond their impact on innovation input, the supply-side and, especially, the demand-side determinants of innovation may affect the relationship between innovation input and innovation output. For instance, a larger market at home or abroad is typically associated with a larger number of competitors. We suspect that the same expenditure on innovation input should face a higher risk of failure in more crowded markets than in less crowded ones. However, what is important here is that the observable variables included in our specifications determine both innovation input and innovation output. Altogether, the benchmark selection models include 43 observables. In some of the sensitivity checks, we will even augment these models and include further variables. Table 2 summarizes mean and standard deviation of all covariates used in the benchmark models.[13]

5 Estimation results

Table 3 presents the results of a bivariate probit model (assuming a bivariate normal cumulative density function, respectively) determining a representative firm's choice of product and/or process innovation. We have also estimated a multinomial logit model (assuming a logistic cumulative density function of the latent outcome variable and that the alternatives are irrelevant for the choices actually taken) details of which we skip here for the sake of brevity.[14]

The log-likelihoods of the bivariate probit and the multinomial logit models are very close as well as are the estimated propensity scores. As a consequence, the treatment effects based on the multinomial logit selection model with radius matching and a radius of 0.05 lead to qualitatively similar conclusions as before, while there is some difference between probit-based and logit-based treatment effects in quantitative terms. Hence, the effects of innovations on exports in the subsequent tables will mostly be based on the bivariate probit.

[12] The notion that trade—and, hence, foreign competition—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).

[13] It also summarizes these moments for innovation expenditures as a share of turnover, which will be used only in the sensitivity analysis.

[14] Results on both the selection model estimates and the corresponding treatment effects on exports are available from the authors upon request.

Table 2 Descriptive statistics

	Mean	S.d.
Firm-level variables		
Exporter in $(t+1)$	0.780	0.414
ln(Turnover) in $t-1$	10.173	1.863
ln(Turnover per worker) in $t-1$	5.364	0.965
Indic.: Lacking own capital	0.294	0.456
Indic.: Lacking external capital	0.227	0.419
Indic.: Long amortization period	0.343	0.475
Indic.: Imperfect cooperation poss.	0.156	0.363
Export share in t	0.963	0.189
Export share in $(t-1)$	0.953	0.212
State of business: mean in year t	2.120	0.516
State of business: s.d. in year t	0.336	0.242
Demand vs. prev. month: mean in year t	2.044	0.308
Demand vs. prev. month: s.d. in year t	0.539	0.252
Existing orders: mean in year t	2.345	0.464
Existing orders: s.d. in year t	0.325	0.247
Innovation expenditures as share of turnover in $(t-1)$	3.981	5.043
Interaction terms of ln(Turnover) in $t-1$ *with*		
log(turnover) in $(t-1)$	106.950	38.587
log(turnover per capita) in $(t-1)$	55.625	16.887
Insufficient own capital	2.962	4.688
Insufficient outside capital	2.278	4.282
Time to break even too long	3.621	5.128
Insufficient cooperation with public, research instit.	1.645	3.891
State of business: mean in year t	21.427	6.123
State of business: s.d. in year t	3.402	2.555
Demand vs. prev. month: mean in year t	20.749	4.698
Demand vs. prev. month: s.d. in year t	5.461	2.767
Existing orders: mean in year t	23.698	5.862
Existing orders: s.d. in year t	3.293	2.607
Interaction terms of log(turnover per capita) in $(t-1)$ *with*		
log(turnover per capita) in $(t-1)$	29.703	9.339
Insufficient own capital	1.552	2.454
Insufficient outside capital	1.197	2.244
Time to break even too long	1.850	2.624
Insufficient cooperation with public, research instit.	0.840	1.987
State of business: mean in year t	11.330	3.303
State of business: s.d. in year t	1.800	1.359
Demand vs. prev. month: mean in year t	10.957	2.529

Table 2 continued

	Mean	S.d.
Demand vs. prev. month: s.d. in year t	2.880	1.456
Existing orders: mean in year t	12.516	3.133
Existing orders: s.d. in year t	1.739	1.385
Sector-level variables		
For Germany		
ln(Value-added) in $t-1$	9.614	0.963
ln(Value-added per worker) in $t-1$	−3.155	0.203
ln(Unit labor cost) in $t-1$	−1.445	0.254
For EU14		
ln(Value-added) in $t-1$	7.917	0.830
ln(Value-added per worker) in $t-1$	−2.998	0.296
ln(Unit labor cost) in $t-1$	−1.797	0.236

Source: Ifo Innovation Survey, 1994-2004, and Ifo Business Survey, 1994–2004. See main text for details

For the bivariate probit model, test statistics indicate that domestic industry variables and weighted EU14 industry variables are group wise and jointly significant at the 1% level in the model.[15] Similarly, the included innovation impediments—main effects and also interactive effects—drawn from data contained in Ifo's Innovation Survey are jointly significant. Finally, the variables based on information in Ifo's Business Survey—including interactive effects—are jointly significant.

In order to verify 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% (Rosenbaum and Rubin 1985).[16] More detail on the balancing tests is provided in an appendix which is not included in the printed version of the article but available online from the authors. Here, we summarize the main findings. In our case, the median bias between the treated and the matched control units amounts to about 9%, 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 25.88 to 8.8 with radius matching and a radius $r = 0.05$. Overall, matching reduces the bias by more than half. 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 0.391, i.e., the covariates are relevant predictors in the overall sample. However, in the matched sample of nearest neighbors,

[15] In the sensitivity analysis, we will summarize results based on models which include fixed sectoral effects (at the 2-digit NACE level).

[16] Note that this heuristic rule for the standardized bias was suggested for some simple versions of matching in the binary treatment case.

Table 3 Product and process innovations: bivariate probit

	Product innovation (1)	Process innovation (2)
Firm-level variables		
log(turnover) in $(t-1)$	0.067 (0.237)	−0.028 (0.216)
log(turnover per capita) in $(t-1)$	0.046 (0.320)	0.197 (0.298)
Insufficient own capital	1.301 (0.650)	0.333 (0.593)
Insufficient outside capital	0.505 (0.682)	0.972 (0.625)
Time to break even too long	0.458 (0.436)	0.341 (0.401)
Insufficient cooperation with public, research instit.	−0.122 (0.544)	−0.423 (0.512)
Export share in t	0.003 (0.206)	0.053 (0.204)
Export share in $(t-1)$	0.237 (0.184)	0.237 (0.182)
State of business: mean in year t	−0.933 (0.562)	−1.590 (0.526)
State of business: s.d. in year t	−0.293 (0.835)	−1.029 (0.782)
Demand vs. prev. month: mean in year t	−0.921 (0.646)	0.043 (0.620)
Demand vs. prev. month: s.d. in year t	1.405 (0.778)	0.072 (0.717)
Existing orders: mean in year t	0.654 (0.636)	0.809 (0.605)
Existing orders: s.d. in year t	0.391 (0.814)	0.543 (0.772)
Interaction terms of ln(Turnover) in $t-1$ with		
log(turnover) in $(t-1)$	0.029 (0.012)	0.012 (0.010)
log(turnover per capita) in $(t-1)$	−0.072 (0.033)	−0.026 (0.030)
Insufficient own capital	−0.080 (0.075)	0.070 (0.069)
Insufficient outside capital	−0.050 (0.085)	−0.170 (0.076)
Time to break even too long	0.063 (0.056)	−0.060 (0.048)
Interaction terms of ln(Turnover) in $t-1$ with		
Insufficient cooperation with public, research instit.	0.062 (0.072)	0.238 (0.067)
State of business: mean in year t	0.014 (0.060)	0.064 (0.054)
State of business: s.d. in year t	−0.040 (0.096)	0.134 (0.087)
Demand vs. prev. month: mean in year t	0.021 (0.076)	0.027 (0.071)
Demand vs. prev. month: s.d. in year t	−0.184 (0.092)	−0.0004 (0.079)
Existing orders: mean in year t	0.063 (0.066)	0.025 (0.059)
Existing orders: s.d. in year t	0.144 (0.093)	0.011 (0.084)
Interaction terms of log(turnover per capita) in $(t-1)$ with		
log(turnover per capita) in $(t-1)$	0.048 (0.025)	0.017 (0.023)
Insufficient own capital	−0.019 (0.128)	−0.126 (0.114)
Insufficient outside capital	−0.003 (0.144)	0.098 (0.127)
Time to break even too long	−0.043 (0.089)	0.185 (0.081)
Insufficient cooperation with public, research instit.	−0.074 (0.117)	−0.320 (0.109)
State of business: mean in year t	0.107 (0.111)	0.131 (0.106)
State of business: s.d. in year t	0.116 (0.170)	−0.067 (0.160)
Demand vs. prev. month: mean in year t	0.079 (0.133)	−0.080 (0.128)
Demand vs. prev. month: s.d. in year t	0.125 (0.149)	−0.004 (0.138)

Table 3 continued

	Product innovation (1)	Process innovation (2)
Existing orders: mean in year t	−0.193 (0.127)	−0.185 (0.120)
Existing orders: s.d. in year t	−0.371 (0.162)	−0.083 (0.152)
Sector-level variables		
For Germany		
ln(Value-added) in $(t-1)$	0.342 (0.094)	0.051 (0.089)
ln(Value-added per worker) in $(t-1)$	−0.660 (0.192)	−0.612 (0.186)
ln(Unit labor cost) in $(t-1)$	1.694 (0.332)	1.064 (0.318)
For EU14		
ln(Value-added) in $(t-1)$	−0.300 (0.125)	0.066 (0.117)
ln(Value-added per worker) in $(t-1)$	−0.084 (0.143)	0.024 (0.141)
ln(Unit labor cost) in $(t-1)$	−1.651 (0.280)	−0.640 (0.270)
Atrho	0.911 (0.041)	
Number of observations	3,401	

Source: Ifo Innovation Survey, 1994–2004, and Ifo business survey, 1994–2004
See main text for details
Note: Standard errors in parentheses

the pseudo-R^2 of the same selection regression drops to 0.074, i.e., in the matched sample, there very little remains systematic difference in observables between treated and control firms. In other words, our matching procedure does a good job in balancing firm and sector characteristics and allows us matching comparable firms as required.

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 differs by not more than the radius from the propensity score of the treated unit they are matched onto. 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 4.

In the above cited table, we report estimates of all the 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

Table 4 Multiple treatment effects: radius matching, $r = 0.05$

T–C	$\widehat{\theta}$ (1)	$\widehat{\sigma}_{\theta}$ (2)	$\widetilde{\widetilde{\sigma}}_{\theta}$ (3)	$\widehat{\alpha}$ (4)	$\widehat{\sigma}_{\alpha}$ (5)	$\widetilde{\widetilde{\sigma}}_{\alpha}$ (6)	$\widehat{\gamma}$ (7)	$\widehat{\sigma}_{\gamma}$ (8)	$\widetilde{\widetilde{\sigma}}_{\gamma}$ (9)
(01) (d, c)–$(0, 0)$	0.070	0.044	0.023	0.087	0.013	0.025	0.088	0.036	0.024
(02) $(0, 0)$–(d, c)	−0.106	0.023	0.039	−0.087	0.013	0.025	−0.088	0.036	0.024
(03) (d, c)–$(0, c)$	0.181	0.058	0.043	0.185	0.049	0.040	0.174	0.023	0.041
(04) $(0, c)$–(d, c)	−0.212	0.038	0.043	−0.185	0.049	0.040	−0.174	0.023	0.041
(05) $(d, 0)$–(d, c)	−0.031	0.019	0.021	−0.023	0.019	0.017	−0.014	0.024	0.024
(06) (d, c)–$(d, 0)$	0.020	0.024	0.016	0.023	0.019	0.017	0.014	0.024	0.024
(07) $(0, 0)$–$(d, 0)$	−0.108	0.030	0.040	−0.090	0.021	0.034	−0.074	0.031	0.027
(08) $(d, 0)$–$(0, 0)$	0.044	0.030	0.027	0.090	0.021	0.034	0.074	0.031	0.027
(09) $(0, 0)$–$(0, c)$	0.052	0.048	0.051	0.055	0.049	0.048	0.087	0.031	0.038
(10) $(0, c)$–$(0, 0)$	−0.079	0.040	0.041	−0.055	0.049	0.048	−0.087	0.031	0.038
(11) $(0, c)$–$(d, 0)$	−0.186	0.043	0.049	−0.162	0.043	0.047	−0.161	0.015	0.042
(12) $(d, 0)$–$(0, c)$	0.154	0.057	0.055	0.162	0.043	0.047	0.161	0.015	0.042

Source: Ifo innovation survey, 1994–2004. Ifo business survey, 1994–2004. See main text for details

T denotes the treatment and 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)

$\widehat{\theta}$, $\widehat{\alpha}$, and $\widehat{\gamma}$ refer to the treatment effect estimates described in the text. For each type of treatment effect, $\widehat{\sigma}$ and $\widetilde{\widetilde{\sigma}}$ refer to the corresponding analytic and sub-sampling-based standard errors. See main text for details

concepts $(\hat{\theta}, \hat{\alpha}, \hat{\gamma})$, the analytic standard errors $(\hat{\sigma}_{\theta}^{a}, \hat{\sigma}_{\alpha}^{a}, \hat{\sigma}_{\gamma}^{a})$, and their sub-sampling-based counterparts $(\hat{\sigma}_{\theta}^{s}, \hat{\sigma}_{\alpha}^{s}, \hat{\sigma}_{\gamma}^{s})$, respectively.[17] Our results indicate that the analytic standard errors are similar to the block sub-sampled ones in the majority of cases and where they differ somewhat more (e.g., when comparing columns (5) and (6) in lines (01) and (02) of Table 4), inference remains largely unchanged. In the subsequent discussion, we will base our inference on analytic standard errors, but we should keep the insights from Table 4 in mind when considering the standard errors.

Overall, the results point to a strong, positive role to play in the case of product innovation for a firm's propensity to export. For instance, firms that conduct new product and process innovations (T is (d, c)) exhibit a significantly higher export propensity than the ones that do neither product nor process innovations (C is (0,0)). The estimates suggest that firms receiving the treatment (d, c) exhibit an export propensity that is about seven 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

[17] We rely on the result found in Abadie and Imbens (2008) that sub-sampling standard errors provide unbiased estimates of the true ones while bootstrapped standard errors do not. Here, we implement block-sub-sampling, inspired by the study of Fitzenberger (1998). Specifically, we draw 1,211 sub-samples of whole observation vectors of firms. During this process, we account for serial correlation over time for a given firm. Innovation activity and exports are quite persistent, which may render simple sub-sampling standard errors as well as analytic ones too low. Block-sub-sampling corrects for autocorrelation in the disturbances.

propensity that is about 11% lower than for ones with treatment (d, c). These two ATTs are significantly different from zero at conventional levels. 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 $\hat{\alpha} \approx 0.09$. Hence, product and process innovation together enhance a firm's export propensity by about nine percentage points. Similar conclusions apply for the ATE: product and process innovation together increase a firm's propensity to export by about $\hat{\gamma} \approx 0.09$—i.e., nine percentage points—irrespective of and unconditional on the type of treatment it actually received.

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) and $(0, c)$, respectively, and the matched control units C receive $(0, c)$ and (d, c), respectively. These point estimates are larger in absolute values than those in the first and second lines, irrespective of whether $\hat{\theta}$, $\hat{\alpha}$, or $\hat{\gamma}$ is considered. Even switching from process to product innovation entails significant positive effects on export propensity (consider the two rows at the bottom of Table 4). 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. In 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 do not exert a positive impact on export propensity (see lines 9–10 in the table).

Is there any gain from matching in this data set? In order shed light on this issue, we may compare the average treatment effect under the assumption of unconditional mean independence, ($\hat{\gamma}_{UMI}$), with its counterpart assuming conditional mean independence as reported in Table 4 ($\hat{\gamma}$). $\hat{\gamma}_{UMI}$ 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 treatment effect estimates (i.e., the simple mean comparisons) together with their $\hat{\gamma}_{CMI}$ counterparts as of Table 4 are summarized in Table 5. Since the average treatment effects are symmetric throughout, we only report every second estimate as compared to Table 4.

It seems worth noting that the sign of $\hat{\gamma}_{UMI}$ is always identical to the one of $\hat{\gamma}$ in our application. For five of the six parameters the (absolute), difference between $\hat{\gamma}_{UMI}$ and $\hat{\gamma}$ is higher than 50% of $\hat{\gamma}$. In many of these cases this, difference is significant. Hence, accounting for self-selection into treatment is quantitatively important in this data set, leading to significantly different average treatment effect estimates.

6 Sensitivity analysis and extension

We undertake several robustness checks to assess the sensitivity of our findings. We may distinguish between two types of checks: first, we assess the sensitivity of the estimated treatment effects *given the specification of selection into innovations*; and second, we look into modifications of the selection models *given the benchmark radius matching procedure*.

Table 5 Average treatment effects under the unconditional and the conditional mean independence assumption

T–C	$\hat{\gamma}_{UIA}$	$\hat{\sigma}^s_{\gamma_{UIA}}$	$\hat{\gamma}$	$\hat{\sigma}^s_{\gamma}$
	(1)	(2)	(3)	(4)
(01) (d, c)–(0, 0)	0.279	0.015	0.088	0.029
(03) (d, c)–$(0, c)$	0.298	0.031	0.174	0.000
(06) (d, c)–$(d, 0)$	0.075	0.021	0.014	0.000
(08) $(d, 0)$–(0, 0)	0.204	0.021	0.074	0.029
(10) $(0, c)$–(0, 0)	−0.019	0.031	−0.087	0.029
(11) $(0, c)$–$(d, 0)$	−0.223	0.034	−0.161	0.000

Source: Ifo Innovation Survey, 1994–2004; and Ifo Business Survey, 1994–2004. See main text for details
UIA refers to the Unconditional Mean Independence Assumption
T denotes the treatment, and 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 reproduced from Table 4

6.1 Alternative matching procedures given the benchmark specification of selection

In these experiments, we only report analytic standard errors of the endogenous treatment effect estimates for the sake of brevity. The corresponding results are reported in Columns from (2) to (6) of Tables 6, 7, and 8. Table 6 summarizes the ATT estimates ($\hat{\theta}^{m,l}$) for all sensitivity checks, Table 7 the estimates of $\hat{\alpha}^{m,l}$, and Table 8 those of ATE ($\hat{\gamma}^{m,l}$). For convenience, we repeat the benchmark estimates from Table 4 in Column (1) of these tables.

First, in Column (2), 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 4. Second, in Column (3), we use a nearest neighbor-matching estimator, where we compare each treated firm's outcome to that of 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 5 or 0.5% points as required with the previous radius matching estimates). Third, in Column (4), we use an Epanechnikov kernel-based matching with a bandwidth of 0.06 instead of the original radius matching. 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. Fourth, in Column (5), we infer to which extent kernel matching depends on the choice of the kernel bandwidth. For this, we choose a much narrower bandwidth of 0.02 which mimics (but is not identical to) the choice of a smaller radius under radius matching. Fifth, in Column (6), we use an alternative kernel, namely a Gaussian one with a bandwidth of 0.06, where $\phi(\Delta/0.06)$ is the kernel weight, $\phi(\cdot)$ is the normal

Table 6 Multiple treatment effects: robustness checks for θ

T–C	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(01) (d, c)–$(0, 0)$	0.070 (0.044)	0.055 (0.053)	0.044 (0.061)	0.069 (0.008)	0.065 (0.008)	0.068 (0.008)	0.065 (0.046)	0.050 (0.048)	0.082 (0.041)	0.062 (0.030)
(03) (d, c)–$(0, c)$	0.181 (0.058)	0.153 (0.067)	0.119 (0.105)	0.172 (0.008)	0.125 (0.008)	0.152 (0.008)	0.176 (0.058)	0.182 (0.074)	0.086 (0.072)	0.057 (0.040)
(06) (d, c)–$(d, 0)$	0.020 (0.024)	0.026 (0.021)	0.026 (0.041)	0.020 (0.008)	0.020 (0.008)	0.020 (0.008)	0.022 (0.024)	0.026 (0.026)	0.009 (0.025)	0.003 (0.019)
(08) $(d, 0)$–$(0, 0)$	0.044 (0.030)	0.022 (0.030)	0.004 (0.040)	0.042 (0.017)	0.032 (0.017)	0.037 (0.017)	0.042 (0.030)	0.010 (0.035)	0.074 (0.030)	0.062 (0.021)
(10) $(0, c)$–$(0, 0)$	−0.079 (0.040)	−0.094 (0.041)	−0.070 (0.055)	−0.080 (0.036)	−0.074 (0.036)	−0.085 (0.036)	−0.084 (0.041)	−0.055 (0.041)	−0.079 (0.043)	0.005 (0.031)
(11) $(0, c)$–$(d, 0)$	−0.186 (0.043)	−0.157 (0.044)	−0.205 (0.053)	−0.186 (0.036)	−0.166 (0.036)	−0.186 (0.036)	−0.185 (0.043)	−0.148 (0.053)	−0.185 (0.043)	−0.110 (0.032)

Source: Ifo innovation survey, 1994–2004; and Ifo business survey, 1994–2004. See main text for details

T denotes the treatment, and 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)

Column (1): Radius matching with $r = 0.05$; Column (2): Radius matching with $r = 0.005$; Column (3): Nearest neighbor matching; Column (4): Kernel matching, Epanechnikov kernel, bandwidth 0.06; Column (5): Kernel matching, Epanechnikov kernel, bandwidth 0.02; Column (6): Kernel matching, Gaussian kernel; Column (7): Radius matching, $r = 0.05$, with control for past innovation expenditures; Column (8): Radius matching, $r = 0.05$, with sector dummies; Column (9): Radius matching, $r = 0.05$, based on multinomial logit model; Column (10): Radius matching, $r = 0.05$, completed innovations only

Table 7 Multiple treatment effects: robustness checks for α

T–C	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(01) (d, c)–(0, 0)	0.087 (0.013)	0.074 (0.014)	0.064 (0.025)	0.087 (0.008)	0.081 (0.008)	0.085 (0.008)	0.086 (0.013)	0.056 (0.014)	0.095 (0.015)	0.088 (0.012)
(03) (d, c)–$(0, c)$	0.185 (0.049)	0.160 (0.044)	0.124 (0.064)	0.176 (0.008)	0.133 (0.008)	0.158 (0.008)	0.180 (0.050)	0.178 (0.074)	0.099 (0.053)	0.067 (0.029)
(06) (d, c)–$(d, 0)$	0.023 (0.019)	0.023 (0.020)	0.021 (0.030)	0.022 (0.007)	0.020 (0.007)	0.022 (0.007)	0.024 (0.019)	0.030 (0.030)	0.013 (0.020)	0.00007 (0.013)
(08) $(d, 0)$–(0, 0)	0.090 (0.021)	0.061 (0.022)	0.073 (0.032)	0.088 (0.011)	0.074 (0.011)	0.082 (0.011)	0.089 (0.021)	0.058 (0.031)	0.112 (0.022)	0.115 (0.016)
(10) $(0, c)$–(0, 0)	−0.055 (0.049)	−0.098 (0.045)	−0.107 (0.065)	−0.057 (0.013)	−0.083 (0.013)	−0.068 (0.013)	−0.053 (0.050)	−0.036 (0.074)	−0.012 (0.053)	0.003 (0.032)
(11) $(0, c)$–$(d, 0)$	−0.162 (0.043)	−0.172 (0.039)	−0.185 (0.056)	−0.161 (0.016)	−0.152 (0.016)	−0.157 (0.016)	−0.169 (0.044)	−0.159 (0.063)	−0.144 (0.046)	−0.087 (0.028)

Source: Ifo innovation survey, 1994–2004; and Ifo business survey, 1994–2004. See main text for details

T denotes the treatment, and 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)

Column (1): Radius matching with $r = 0.05$; Column (2): Radius matching with $r = 0.005$; Column (3): Nearest neighbor matching; Column (4): Kernel matching, Epanechnikov kernel, bandwidth 0.06; Column (5): Kernel matching, Epanechnikov kernel, bandwidth 0.02; Column (6): Kernel matching, Gaussian kernel; Column (7): Radius matching, $r = 0.05$, with control for past innovation expenditures; Column (8): Radius matching, $r = 0.05$, with sector dummies; Column (9): Radius matching, $r = 0.05$, based on multinomial logit model; Column (10): Radius matching, $r = 0.05$, completed innovations only

Table 8 Multiple treatment effects: robustness checks for γ

T–C	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(01) (d, c)–$(0, 0)$	0.088 (0.036)	0.071 (0.038)	0.058 (0.050)	0.087 (0.022)	0.080 (0.022)	0.084 (0.022)	0.087 (0.037)	0.057 (0.041)	0.096 (0.038)	0.085 (0.036)
(03) (d, c)–$(0, c)$	0.174 (0.023)	0.178 (0.025)	0.161 (0.035)	0.170 (0.015)	0.158 (0.015)	0.164 (0.015)	0.174 (0.023)	0.150 (0.026)	0.111 (0.025)	0.085 (0.014)
(06) (d, c)–$(d, 0)$	0.014 (0.024)	0.023 (0.025)	0.005 (0.035)	0.014 (0.015)	0.017 (0.015)	0.015 (0.015)	0.016 (0.024)	0.011 (0.027)	0.0008 (0.026)	−0.015 (0.015)
(08) $(d, 0)$–$(0, 0)$	0.074 (0.031)	0.048 (0.033)	0.053 (0.040)	0.073 (0.021)	0.063 (0.021)	0.069 (0.021)	0.071 (0.032)	0.046 (0.035)	0.096 (0.033)	0.100 (0.035)
(10) $(0, c)$–$(0, 0)$	−0.087 (0.031)	−0.107 (0.032)	−0.103 (0.039)	−0.084 (0.021)	−0.078 (0.021)	−0.080 (0.021)	−0.087 (0.031)	−0.093 (0.034)	−0.015 (0.032)	0.0001 (0.035)
(11) $(0, c)$–$(d, 0)$	−0.161 (0.015)	−0.154 (0.014)	−0.156 (0.017)	−0.157 (0.013)	−0.141 (0.013)	−0.150 (0.013)	−0.158 (0.015)	−0.139 (0.017)	−0.110 (0.015)	−0.100 (0.013)

Source: Ifo innovation survey, 1994–2004; and Ifo Business survey, 1994–2004. See main text for details

T denotes the treatment, and 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)

Column (1): Radius matching with $r = 0.05$; Column (2): Radius matching with $r = 0.005$; Column (3): Nearest neighbor matching; Column (4): Kernel matching, Epanechnikov kernel, bandwidth 0.06; Column (5): Kernel matching, Epanechnikov kernel, bandwidth 0.02; Column (6): Kernel matching, Gaussian kernel; Column (7): Radius matching, $r = 0.05$, with control for past innovation expenditures; Column (8): Radius matching, $r = 0.05$, with sector dummies; Column (9): Radius matching, $r = 0.05$, based on multinomial logit model; Column (10): Radius matching, $r = 0.05$, completed innovations only

density, and Δ is the absolute difference in propensity scores between a treated and a control unit.

Let us start with summarizing the findings for the ATT estimates. Across the board, neither changing the radius nor the matching estimator (nearest neighbor- or alternative kernel-matching estimators with different bandwidths instead of radius matching) affects our conclusions from above. Although the estimated treatment effects differ somewhat in size, the qualitative pattern is the same.

Similar conclusions apply for the estimates in Tables 7 and 8. Overall, neither the alternative values for the radius, nor the type of the matching estimator (radius versus nearest neighbor versus kernel), the kernel bandwidths, or the functional forms of the kernels have a qualitative impact on the significant findings in the original table.

Finally, we also investigated the question of how innovations affect the extensive margin of exports in year $t+2$ or $t+3$ as compared to exports in $t+1$ in the benchmark case. Space constraints do not permit a comprehensive summary of the corresponding estimates, but let us mention a few general results. For instance, the average treatment effect $\widehat{\gamma}^{(d,c)--(0,0)}$ was 0.088 for exports in $t + 1$ in the benchmark results, and amounts to 0.085 for exports in $t + 2$ and to 0.099 for exports in $t + 3$. Moreover, $\widehat{\gamma}^{(d,0)--(0,0)}$ was 0.074 in Table 4, and amounts to 0.086 for exports in $t + 2$ and to 0.040 for exports in $t + 3$. Finally, $\widehat{\gamma}^{(d,0)--(0,c)}$ was 0.161 in Table 4, and amounts to 0.063 for exports in $t + 2$ and to 0.075 for exports in $t + 3$. Hence, there is not much difference to the magnitude of the impact of innovations in period t on the extensive export margin in $t + 1$ as compared to the one in $t + 2$ or $t + 3$.

Overall, the results in Table 4, are robust with regard to the changes discussed here. There is neither much difference in the point estimates nor their standard errors for a given treatment effect across most of the columns in any of the Tables 6, 7, and 8.

6.2 Alternative specifications of selection given the benchmark radius matching

We also run a set of alternative selection models to assess the robustness of the previous estimates with regard to modifications of the selection model. Again, the results are summarized in Tables 6, 7, and 8, namely, in Columns (7)–(10). The considered modifications of the selection model relate to the inclusion of additional observable variables determining innovation, the assumed functional form of the underlying latent selection process, and an alternative definition of the product and process innovation indicator variables.

With regard to additional possibly relevant covariates, an explicit measure of innovation input prior to innovation output may be suitable. Notice that we have included a variety of supply and demand factors determining innovation input as well as output in the benchmark selection model in Table 3. Accordingly, we may view the benchmark selection equations as a reduced-form version of a model which accounts for innovation input as well as other determinants of innovation output. However, we may use the time structure of the data and include expenditures on innovation activities in the year prior to potential innovation output as a direct measure of input costs of innovation. We include the expenditures for innovation expenses for the relevant product line ("Innovationsaufwendungen für den Erzeugnisbereich in Prozent vom Umsatz") from ifo's Innovation Survey in the bivariate probit model underlying the treatment effect estimates in Column (7) of Tables 6, 7, and 8. In particular, we include this variable in addition to the ones that had been employed before. Hence, this and the other variables together serve as a catch-all of innovation input costs and other determinants of innovation output at given input. In Column (8), we include NACE 2-digit sector-specific fixed effects in the bivariate probit selection model in addition to all those variables included in Column (7)—altogether, this model includes the 43 variables from the benchmark model plus 21 sector dummies. In Column (9), we summarize treatment effect estimates that are based on the multinomial logit model which we have mentioned before. Finally, Column (10) reflects estimates which are based on the same specification of the right-hand side of the bivariate probit selection model as in Table 3 but uses alternatively defined product and process innovation indicators; while the indicators in the benchmark results reflected ongoing as well as finished innovations, we confine our interest to the effects of completed innovations on exports in Column (10). For reasons of space, we do not show estimates of the alternative selection models underlying the treatment effects in Columns (7)–(10) here.[18]

Again, it turns out that the modifications do not alter the original conclusions for the treatment effects in qualitative terms. Moreover, the magnitude of the estimated treatment effects is remarkably stable across the sensitivity checks. Hence, neither an omission of a direct measure of innovation input costs nor fixed sectoral effects, using a multinomial logit instead of a bivariate probit, nor focusing on completed rather than completed as well as ongoing innovations has much bearing for the conclusions drawn before.[19] Altogether, we may conclude that the results are robust with regard to the mentioned changes.

While our primary focus is on a firm's propensity to export at all, the so-called *extensive margin* of exporting, we also considered effects on the *intensive margin* of exporting, measured as the fraction of exports in total plant sales (see Wakelin 1997, 1998, for a similar exercise when assuming exogenous innovations). While we do not report the treatment effects in table format for the sake of brevity, two results are worth mentioning. First, process innovations are qualitatively more important for the export-to-sales ratio than they are for the decision to export at all. Second, process innovations alone lead to a decline in the probability of exporting at all, while they too have a positive effect on the intensive margin on their own.

In general, this article thus provides evidence that product innovation is more important than process innovation for a firm's decision to export at all (export propensity). However, while process innovation seems of little relevance for export propensity, it

[18] However, we would like to mention that innovation expenditures as a measure of innovation input enters insignificantly in the selection equation of product innovations but positively (and significantly different from zero at conventional levels) in the process innovation model underlying Column (7). Accordingly, we may conclude that the observables included in the benchmark models capture the impact of innovation input costs on product innovations in a comprehensive way, while this is not the case for process innovations. The sectoral fixed effects are jointly significant in both the process and the product innovation selection equation underlying Column (8).

[19] We find that the impact of innovations on the extensive margin of exports tends to be somewhat smaller if we use completed innovations only.

improves a firm's probability to export if it is accompanied by product innovation. This evidence is robust along a variety of dimensions mentioned above.

7 Conclusions

Our aim in this article 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 study. 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 study 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 of innovations—product and process innovations—one is then faced with an econometric framework with multiple endogenous treatments.

Adopting a statistical 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 the extensive margin of exports when ignoring self-selection into either mode of innovation. This bias was positive and quite substantial in our application, having been particularly large for firms with only product or process innovations as compared to firms that did not innovate. The largest estimated self-selection upward-bias in the data amounted to more than 200%, 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 for the decision to export. Firms that perform both process and product innovation have a higher probability to export than firms that do not innovate; however, when performed alone, product innovation is more determinant in the exporting behavior of a firm than is process 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. While process innovations increase a firm's probability to export only when being combined with product innovations, they marginally raise a firm's export-to-sales ratio at the intensive margin.

As regards possible conclusions for economic policy, our findings suggest that policy instruments should be targeted towards specific innovations rather than innovation input, in general, if exporting is at stake. In particular, subsidies and other programs aiming at product innovations—eventually combined with process innovations—will on average be more likely to cause entry into export markets than expenditures or legal environments which particularly favor process innovations.

Acknowledgements We would like to thank the participants at the workshop *Globalization Effects on Firms and Workers* at the University of Nottingham, the WEA Pacific Rim Conference in Beijing, the ESEM Budapest, and the EARIE Conference in Valencia, for comments on an earlier draft. In particular, we are indebted to the editor and two anonymous referees of Empirical Economics as well as to Stefan Lachenmaier and Zhihong Yu for helpful suggestions.

References

Abadie A, Imbens GW (2008) On the failure of the bootstrap for matching estimators. Econometrica 76:1537–1557
Atkeson A, Burstein A (2007) Innovation, firm dynamics, and international trade. NBER working paper no. 13326
Aw BY, Roberts MJ, Winston T (2007) Export market participation, investments in R&D and worker training, and the evolution of firm productivity. World Econ 14:83–104
Aw BY, Roberts MJ, Xu DY (2009) R&D investment, exporting, and productivity dynamics. NBER working paper no. 14670
Baily MN, Gersbach H (1995) Efficiency in manufacturing and the need for global competition. Brookings Papers on Economic Activity: Microeconomics, pp 307–358
Basile R (2001) Export behavior of Italian manufacturing firms over the nineties: the role of innovation. Res Policy 30:1185–1201
Becker SO, Wohlrabe K (2008) Micro data at the ifo institute for economic research-f́b-the "ifo business survey"—usage and access. Schmollers Jahrbuch 128:307–319
Bernard A, Jensen JB (1997) Exporters, skill upgrading, and the wage gap. J Int Econ 42:3–31
Bernard A, Jensen JB (1999) Exceptional export performance: cause, effect, or both? J Int Econ 47:1–25
Boone J (2000) Competitive pressure: the effects on investments in product and process innovation. RAND J Econ 31(3):549–569
Braunerhjelm P (1996) The relation between firm specific intangibles and exports. Econ Lett 53:213–219
Cassiman B, Martínez-Ros E (2007) Innovation and exports: evidence from Spanish manufacturing. Unpublished manuscript, IESE Business School
Cohen WM, Klepper S (1996) Firm size and the nature of innovation within industries: the case of process and product R&D. Rev Econ Stat 78:232–243
Constantini JA, Melitz MJ (2008) The dynamics of firm-level adjustment to trade liberalization. In: Helpman E, Marin D, Verdier T (eds) The organization of firms in a global economy. Harvard University Press, Cambridge, MA
Dehejia RH, Wahba S (1999) Causal effects in non-experimental studies: reevaluating the evaluation of training programmes. J Am Stat Assoc 94:1053–1062
Dehejia RH, Wahba S (2002) Propensity score matching methods for non-experimental causal studies. Rev Econ Stat 84:151–161
Dollar D (1986) Technological innovation, capital mobility, and the product cycle in North-South trade. Am Econ Rev 76:177–190
Ebling G, Janz N (1999) Export and innovation activities in the German service sector. Empirical evidence at the firm level. ZEW discussion paper no. 99–53, Zentrum fur Europäische Wirtschaftsforschung, Mannheim
Entorf H, Krader W, Pohlmeier W (1988) Entscheidungen über Innovation, Beschäftigung und Außenhandel: Empirische Ergebnisse eines simultanen Probitansatzes. In: Kräger H (ed) Empirische Wirtschaftsforschung, Heinz König zum 60. Frankfurt am Main, Geburtstag, pp 27–47
Fitzenberger B (1998) The moving blocks bootstrap and robust inference for linear least squares and quantile regressions. J Econ 82:235–287
Flaig G, Stadler M (1994) Success breeds success. The dynamics of the innovation process. Empir Econ 19:55–68
Foellmi R, Zweimüller J (2006) Mass consumption, exclusion, and unemployment. University of Zurich IEW working paper no. 296
Grossman GM, Helpman E (1989) Product development and international trade. J Political Econ 97: 1261–1283
Grossman GM, Helpman E (1990) Comparative advantage and long-run growth. Am Econ Rev 80:796–815
Grossman GM, Helpman E (1991) Innovation and growth in the global economy. MIT Press, Cambridge, MA
Grossman GM, Helpman E, Szeidl A (2006) Optimal integration strategies for the multinational firm. J Int Econ 70:216–238
Heckman JJ, Ichimura H, Todd PE (1997) Matching as an econometric evaluation estimator: evidence from a job training programme. Rev Econ Stud 64:605–654
Heckman JJ, Ichimura H, Todd PE (1998) Matching as an econometric evaluation estimator. Rev Econ Stud 65:261–294

Heckman JJ, LaLonde RJ, Smith JA (1999) The economics and econometrics of active labor market programs. In: Ashenfelter O, Card D (eds) Handbook of labor economics, vol III. Elsevier, New York, pp 1865–2073

Hirsch S, Bijaoui I (1985) R&D Intensity and export performance: a micro view. Weltwirtsch Arch 121: 138–151

Hopenhayn HA (1992) Entry, exit, and firm dynamics in long run equilibrium. Econometrica 60:1127–1150

Hughes KS (1986) Exports and innovation. Eur Econ Rev 30:383–399

Iacovone L, Javorcik BS (2007) Getting ready: preparation for exporting. Unpublished manuscript, Oxford University

Jensen R, Thursby M (1987) A decision theoretic model of innovation, technology transfer, and trade. Rev Econ Stud 54:631–647

Jovanovic B (1982) Selection and the evolution of industry. Econometrica 50:649–670

Kumar N, Siddharthan NS (1994) Technology, firm size and export behavior in developing countries: the case of Indian enterprise. J Dev Stud 32:288–309

Lachenmaier S, Wößmann LW (2006) Does innovation cause exports? Evidence from exogenous innovation impulses and obstacles using German micro data. Oxford Econ Pap 58:317–350

Lachenmaier S, Rottmann H (2007) Employment effects of innovation at the firm level. Jahrbücher für Nationalökonomie und Statistik 227:254–272

Leamer EE, Levinsohn J (1995) International trade theory: the evidence. In: Grossman GM, Rogoff K (eds) The handbook of international economics, vol III. Elsevier, New York, pp 1339–1394

Lechner M (2001) Identification and estimation of causal effects of multiple treatments under the conditional independence assumption. In: Lechner M, Pfeiffer F (eds) Econometric evaluation of labor market policies, vol 13. ZEW Econ Stud, pp 43–58

Lee M-J (2005) Micro-econometrics for policy, program and treatment effects. Oxford University Press, Oxford

Lileeva A, Trefler D (2007) Improved access to foreign markets raises plant-level productivity...for some plants. NBER working paper no. 13297

Martin S (1993) Endogenous firm efficiency in a Cournot principal-agent model. J Econ Theory 59:445–450

Melitz MJ (2003) The impact of trade on intra-industry reallocations and aggregate industry productivity. Econometrica 71:1695–1725

Peters B (2007) Persistence of innovation: stylised facts and panel data evidence. J Tech Transf 34:226–243

Politis DN, Romano JP, Wolf M (1999) Subsampling. Springer, New York

Roper S, Love JH (2002) Innovation and export performance: evidence from the UK and German manufacturing plants. Res Policy 31:1087–1102

Rosenbaum PR, Rubin DB (1985) Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. Am Stat 39:33–38

Schlegelmilch BB, Crook JN (1988) Firm-level determinants of export intensity. Manag Decis Econ 9: 291–300

Segerstrom PS, Anant TCA, Dinopoulos E (1990) A Schumpeterian model of the product life cycle. Am Econ Rev 80:1077–1091

Smith JA, Todd PE (2005) Does matching overcome Lalonde's critique of nonexperimental estimators?. J Econ 125:305–353

Smolny W (1998) Innovations, prices and employment, a theoretical model and an empirical application for West German manufacturing firms. J Ind Econ 46:359–381

Smolny W, Schneeweis T (1999) Innovation, Wachstum und Beschäftigung. Eine empirische Untersucung auf Basis des ifo Unternehmenspanels. Jahrbücher für Nationalökonomie und Statistik 218:453–472

Spence M (1984) Cost reduction, competition, and industry performance. Econometrica 52:101–122

Spencer BJ, Brander JA (1983) International R&D rivalry and industrial strategy. Rev Econ Stud 50(4): 707–722

Wagner J (1996) Export performance, human capital, and product innovation in Germany: a micro view. Jahrbuch für Wirtschaftswissenschaften 47:40–45

Wakelin K (1997) Trade and innovation, theory and evidence. Cheltenham

Wakelin K (1998) Innovation and export behaviour at the firm level. Res Policy 26:829–841

Wooldridge JM (2002) Econometric analysis of cross-section and panel data. MIT Press, Cambridge, MA