UNU-MERIT Working Paper Series

#2014-033

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UNU-MERIT Working Papers

ISSN 1871-9872

Maastricht Economic and social Research Institute on Innovation and Technology, UNU-MERIT

Maastricht Graduate School of Governance MGSoG

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ABSTRACT

This study investigates the impact of innovation support programmes on SME innovation in traditional manufacturing industries in seven EU regions. Recent literature identifying sources of potential government failure in innovation policy suggests that the effects of public support measures to increase private innovation may be disappointing. Our results are consistent with this hypothesis, yet also suggest a direction for policy reform to overcome government failure and, thereby, to increase the potential additionality of innovation support programmes. Innovation support programmes in the EU typically adopt a “cream skimming” selection strategy: namely, programme managers systematically select firms on the basis of observable characteristics conducive to innovation. The econometric analysis of a new survey database reported in this paper suggests that “cream skimming” leads to firms being selected for programme participation that benefit less than would randomly selected firms. The policy corollary is that, subject to due diligence checking, allocation of innovation support by lottery should give rise to greater programme additionality than does the prevalent "cream skimming" approach. We conclude with some practical guidelines for allocation by lottery, which were developed for a recently launched innovation support programme for SMEs.

Key words: innovation; SMEs; traditional manufacturing industry; public innovation support; government failure; evaluation.

JEL Classification: O32, O38, C34, C14

1. INTRODUCTION

This paper reports the first evaluation of the effectiveness of public innovation support programmes for small and medium enterprises (SMEs) in traditional manufacturing industries. Throughout the European Union, there are around 400 such programmes. Yet, in the absence of best practice evaluation, they are of unknown effectiveness, which precludes identification and spreading of best practice (OECD, 2007, pp.11 and 27; also, pp.50 and 52; see also Lenihan et al., 2007). Responding to this lacuna, the European Commission's DG Research commissioned the multi-methods GPrix project.[1] The quantitative dimension of the evaluation required a new questionnaire survey. This paper reports the econometric analysis of the survey database, which informed the main GPrix policy recommendations.

In recent years, empirical analysis of the impact of public support on firms' innovative activities has been mainly concerned with additionality/crowding out. Most empirical studies investigate input additionality, i.e. the effect of subsidies on firms' R&D expenditure. Our study, in contrast, focuses on output additionality, by which we mean the effect of subsidies on firms' innovation: operational innovations (product, process, marketing and organizational innovations);[2] and innovative sales (sales resulting from product and/or process innovations).

The main challenge to innovation policy evaluation is the potential endogeneity of programme participation and its corollary, selection bias. Firms' innovation and a receipt of public subsidies are likely to be codetermined, because both are influenced not only by the observable characteristics of firms (those available to researchers such as measures of firm size) but also by unobservable characteristics (those generally not available to researchers such as management quality). In principle (Curran and Storey, 2002), support may be endogenous to innovation either because firms that are more innovative are more likely to apply for a subsidy (self-selection of firms) and/or firms that are more innovative are more likely to receive a subsidy (government agencies select firms for participation by "cream skimming").[3] In either case, favourable (unfavourable) observable and/or unobservable characteristics may increase (decrease) both firms' participation in support programmes and their innovation behaviour. This introduces

[1] GPrix is fully referenced in the Acknowledgements, below. The project research and corresponding policy recommendations are all described and available from the project website: http://www.gprix.eu/ (under the "Reports" tab). For the extent and variety of innovation support programmes, see the GPrix homepage. Section 3 below defines and discusses "best practice" approaches to the evaluation of programme effectiveness. Extensive discussion and definition of the concept of "traditional manufacturing industry" is provided in GPrix Deliverables 1.1 and 1.2 (2010a & 2010b). For the continued importance of traditional manufacturing industry in most EU regions, see GPrix Deliverable 2.2 (2012a).

[2] For these definitions, see *Oslo Manual* (OECD, 2005).

selection bias into programme evaluation. If evaluators assume that public funding is exogenous with respect to firms' innovation behaviour then they will mistakenly attribute influences arising from underlying observable and unobservable firm characteristics to programme participation, which causes the impact of programme participation to be overestimated. To address programme endogeneity and consequent selection bias in policy evaluation, various empirical strategies are employed. The major distinction between them lies in the treatment of the unobservable heterogeneity of firms. Matching methods, which are most commonly used, can only control for observables, whereas selection models control for both selection on observables and selection on unobservables (Cerulli and Poti, 2008; Czarnitzki and Lopes Bento, 2013). Our preferred approach is the selection model supplemented by matching estimates as a robustness check.

In the next section, we discuss the existing literature on input and output additionality, although we focus on those studies that investigate output additionality. In addition, we briefly survey sources of potential government failure in innovation policy that, together, suggest reasons why public support programmes may fail to achieve additionality. Section 3 examines the methodology, model and the data. Section 4 discusses the results. Section 5 concludes with policy recommendations and sets out some broad principles for their enactment.

2. LITERATURE REVIEW AND HYPOTHESIS

In this paper, in line with Cerulli and Poti (2008), we define additionality as innovation induced by a support programme that would not otherwise have occurred; full crowding out refers to 'a complete substitution of private by public funds', and in our case means that firms' total innovation 'would be the same with or without subsidies' (Gonzales and Pazo, 2008, p. 372); and partial crowding out refers to a partial substitution of private spending, whereby firms raise their total innovation, but by an amount smaller than the subsidy itself (Busom, 2000; Cerulli and Poti, 2008; Streicher et al., 2004).

Following Garcia-Quevedo (2004), theoretical consideration of additionality versus crowding-out effects of private innovation subsidies suggest that both are plausible.[4] David et al. (2000) provide an extensive review of empirical evidence regarding the effect of public support on

[3] The terms "cream skimming", "cherry-picking" and "picking winners" are synonyms.
[4] Most empirical research deals with R&D subsidies, because public policy was - and largely remains - focused on R&D activities, rather than on innovation in the broader context defined by the OECD *Oslo Manual* (2005).

innovation and conclude that, although more empirical studies indicate complementarity than substitutability between public and private R&D funding, the overall conclusion is still ambiguous. Lööf and Heshmati (2007) in their review draw the same conclusion. The meta-analysis conducted by Garcia-Quevedo (2004) also does not provide a definite answer; the results indicate very weak evidence of crowding-out. Most individual studies reject full crowding out (Aerts and Schmidt, 2008; Almus and Czarnitzki, 2003; Cerulli and Poti, 2008; Czarnitzki and Lopes Bento, 2010; Czarnitzki and Lopes-Bento, 2013; Gonzales and Pazo, 2008; Heijs and Herrera, 2004; Lööf and Heshmati, 2007). Yet somewhat different results are reported by Busom (2000) for the impact of public subsidies on the R&D intensity of Spanish firms in 1988: she finds overall additionality, although for 30 per cent of participating firms a full crowding out effect cannot be rejected.

Like evaluations focussed on input additionality, those investigating output additionality yield heterogeneous results (for review see Antonioli and Marzucchi, 2012; Cunningham et al., 2012). However, whether negative or positive, the programme effects are small. Catozzella and Vivarelli (2011) estimate the impact of public support on innovative productivity - the ratio of innovative sales to innovative expenditures - by analysing the third Community Innovation Survey (CIS) dataset for Italy. The model is estimated using a bivariate endogenous switching model, which yields an average treatment on the treated (ATT) effect of -4.95 percentage points. Similarly, Garcia and Mohnen (2010) explore the impact of public support on both product innovation and innovative sales in Austrian firms using the CIS3 dataset. Their results vary depending on the source of funding: EU support has no effect; but central government support has a positive effect on both product innovation and innovative sales. To anticipate, not only are the findings from Catozzella and Vivarelli (2011) in line with our own empirical findings of a small negative ATT effect on product innovation but, in addition, the finding of Garcia and Mohnen (2010) of a positive effect of public support on innovative sales is consistent with the results reported below. Our study encompasses all four innovation modes (product, process, organizational and marketing innovations), which we refer to as operational innovations, as well as innovative sales.

Comparison between public policy evaluations is hampered not only by heterogeneous outcome variables but also by a lack of a common methodology. Best practice evaluation methodology is characterized by the use of a control group – or, at least – a comparison group as the platform for a serious approach to selection bias: Garcia-Quevedo (2004) insist that government support should always be treated as endogenous. As Lööf and Heshmati (2007, p.83) observe: 'It is well documented in the literature that firms funded by the government are likely to be among those with the best ideas.' To address the ubiquity of selection bias, most studies apply the matching estimator (Gonzales and Pazo, 2008; Hussinger, 2008). The drawback of this method is that unobserved heterogeneity among participating firms cannot be controlled for when cross-sectional data are used. This problem is addressed by selection (switching) models (Aakvik et al., 2005), which control for both observed and unobserved heterogeneity. On the other hand, selection models are based on strong distributional assumptions (see Section 5 below), which are not required by the matching method (Hussinger, 2008).

Very few studies use different evaluation methods to check the robustness of their results; two exceptions are Hujer and Radic (2005) and Cerulli and Poti (2012).[5] Hujer and Radic (2005) investigate how public subsidy affects product innovation in Germany by applying matching methods, a selection model and, finally, the difference-in-difference estimator. The results are striking; while additionality is found using the matching method (the ATT effect is positive and significant), it can be rejected when other methods are applied. The authors conclude that neglecting selection bias due to unobservable firm characteristics results in an overestimation of the treatment effect. This finding is consistent with Greene's (2009) conjecture that evaluation methods controlling for unobservable influences find smaller programme effects than do methods controlling only for observable influences. Moreover, Papa (2012) investigated input additionality drawing from the Italian CIS3 data by applying an endogenous switching type II tobit-model. The results echo our own non-rejection of crowding out effects (reported below). The author hypothesizes that the reason why previous studies on Italian firms found evidence of additionality could be because 'essential heterogeneity' was not taken into account (Pepa, 2012, p. 240).

One reason for this lack of robustness checking is that valid instruments cannot be found in the cross-sectional survey datasets typically available to researchers, which precludes the estimation of selection models designed to address selection bias arising from firms’ unobservable characteristics. The present study is likewise limited to cross-sectional data. However, in order to address endogeneity/selection bias, our questionnaire survey was designed to generate valid instruments for a switching model (see Section 3 below). By estimating a switching model, we follow the suggestion of Hujer and Radic (2005) that evaluation of public measures should account for both observable and unobservable characteristics to avoid overestimation of the

[5] Because Cerulli and Poti (2012) investigate input additionality, we do not comment on their findings.

treatment effect when unobservables are not taken into account. However, as a robustness check, we also briefly report the results of applying matching estimators to our data (see Section 4 below).

2.1 GOVERNMENT FAILURE IN INNOVATION POLICY

Many empirical studies[6] note that governments might follow a "picking winners" strategy (Czarnitzki and Lopes-Bento, 2013; Nooteboom and Stam, 2008; Zunica-Vicente et al., 2012), but empirical evidence suggest that the effects of various programmes are, at best, rather small. In this section, we consider reasons for the lack of substantial additionality - even a “crowding out” effect - of public support. As Stiglitz and Wallsten (1999, p. 58) note: "Ironically, underlying the current drive for private-public partnerships is the widespread belief that government is not very effective in choosing good projects (i.e., picking winners) and managing research."

The rationale for the provision of support measures arises from the occurrence of market failures. However, public interventions to mitigate market inefficiency can be impaired by various "government failures" (Nooteboom and Stam, 2008; Stiglitz and Wallsten, 1999; Wallsten, 2000). Firstly, due to measurement difficulties and asymmetric information, public agencies are hampered in selecting those firms with promising innovative projects that would not be undertaken without public support. Secondly, public agencies might be captured by the private interests of lobby groups. Thirdly, even in the presence of perfect information and making decisions independently, public choice theory suggests that public agencies would have incentives to “cream skim” – i.e. to subsidise those firms likely to do research and innovate in any case - to maximize apparent commercial returns and so justify and perpetuate agency resources. Fourthly, according to Wallsten (2000) adverse selection of inframarginal projects (those that generate positive private returns and would be undertaken by firms even without a public intervention) rather than marginal innovation projects (those that are not profitable for firms yet entail social benefits) arises because risk-averse governments fear loss of electoral support as a consequence of selecting programmes with higher probability of failure. Finally, Crespi and Antonelli (2012) suggest another form of government failure related to asymmetric information. The so called "Matthew effect" arises when public agencies select firms based on their previous record of programme participation. In particular, programme managers have difficulties in assessing applications with a low level of scientific content and may accordingly

[6] Several studies empirically confirm this argument (Heijs, 2003; Cantner and Kosters, 2009; Hussinger, 2008).

rely on the firm's past record of programme participation. Together, these forms of potential government failure lead us to hypothesize that the estimated representative effects of public support measures to increase private innovation may be disappointing compared to the effects typically claimed by public agencies.

3. THE MODEL, ESTIMATION AND DATA

3.1 THE MODEL AND ESTIMATION

This section sets out a parsimonious model for econometric estimation of the innovation effects of programme participation on SMEs. This model was first set out publicly in Deliverable 1.3 of the GPrix project (GPrix, 2010c, pp.11-21). Prepublication of models helps to assure the validity of results from subsequent estimation. By setting out our model in advance of data analysis, we limit our options with respect to specification search, which is a well-known source of publication or selection bias in econometric literatures (Stanley, 2005).

The first problem to address is that there are many potential control variables (Becheikh et al., 2006 identify over 60 determinants of innovation). Moreover, even within disciplines, let alone between them, there is no "canonical" model of the determinants of firms' innovation. In the absence of such a model, we propose a strategy for specifying a "parsimonious" model.

1. We use dummy variables wherever possible to aggregate the effects of the many possible individual effects. *Country dummy variables* control for all country effects (i.e., all those variables associated with the "national innovation systems" approach as well as with other institutional effects and with macroeconomic effects); *Regional dummies* substitute for all regional effects (i.e., all those variables associated with the "regional innovation systems" approach); and *Industry dummies* substitute for all industry effects (i.e., all those variables associated with the "technological regimes" approach, e.g., technological opportunities and appropriability conditions, and demand conditions, etc).
2. We use *firm level "quasi" fixed effects* (or initial conditions) to capture *otherwise unobservable* firm and ownership effects. Here we adapt an approach suggested by Blundell et al. (1995); namely, we propose aggregating most time invariant (or, at least, "slow moving") firm-level and ownership influences on innovation by *'including a variable in the regression that approximates the build-up of knowledge of the firm at its point of entry into the sample'* (p.338). According to Blundell et al. (1995, p.338), such a proxy for 'the "permanent" capacities of companies successfully to commercialize new products and

processes' is designed to capture the aggregate effect of firm-level time invariant influences on innovation.

In this approach, there is a crucial assumption; namely, that the variables substituted by country, regional and industry fixed effects, or by firm "quasi" fixed effects, are time invariant or, at least (to use a phrase from Blundell et al., 1995), "slow moving". Our intention to evaluate programmes recently undertaken by firms (from 2005 to 2009) helps to make this assumption more reasonable than if we were taking a very long period into consideration.

Our basic model has two equations: the second equation models the participation decision (the probability that a firm will participate in an innovation support programme); and the first equation is an innovation model, which estimates the innovation effect on firms of participating in an innovation support programme conditional on both other influences on innovation and the probability of participating in an innovation support programme.

$$\begin{aligned}
Innovation_i &= \hat{C} + \hat{\gamma} Participation_i + \hat{\beta}_1 Size_i + \hat{\beta}_2 MPower_i + \hat{\beta}_3 Export_i \\
&\quad + Industry_I \hat{\phi}_1 + Region_R \hat{\phi}_2 + Country_C \hat{\phi}_3 \\
&\quad + QFFE_i \hat{\alpha} + u_i \qquad (1) \\
Participation_i &= \hat{I} + \hat{\lambda}_1 Size_i + \hat{\lambda}_2 MPower_i + \hat{\lambda}_3 Export_i \\
&\quad + Industry_I \hat{\rho}_1 + Region_R \hat{\rho}_2 + Country_C \hat{\rho}_3 + QFFE_i \hat{\delta} \\
&\quad + Obstacle_i \hat{\theta} + \varepsilon_i \qquad (2)
\end{aligned}$$

Subscript *i* indexes each firm in the sample 1…n, where n is the number of firms; ^ indicates "to be estimated"; *C* and *I* represent the intercept in equations 1 and 2 respectively; the γ coefficient measures the innovation effect of programme participation; the β and λ coefficients measure, respectively, the innovation and participation effects of control variables commonly identified in the literature (firm size, market power and the proportion of turnover exported); the k×1 ϕ and ρ vectors contain coefficients that measure, respectively, the innovation and participation effects of 1×k vectors of *Industry*, *Region* and *Country* dummies, where subscripts *I*, *R* and *C* index industries, regions and countries, respectively; the k×1 α and δ vectors contain coefficients that measure, respectively, the innovation and participation effects of 1×k vectors of firm level 'quasi' fixed effects; the k×1 θ vector contains coefficients that measure the participation effects of a 1×k vector of indicators of firms' views on factors promoting or impeding programme participation (*Obstacle*), which are the anticipated identifying variables;

and u and ε are the error terms, which capture the unobserved influences on the respective dependent variables. Full definitions and descriptive statistics for each variable are presented in Appendix A and in Appendix B, Table B.1.

The pre-published baseline model includes only variables common to both the GPrix and the MAPEER database.[7] We also specify a (slightly) *augmented* model by including a variable arising from a question included in the GPrix survey but not in the MAPEER survey: *Collaboration* (=1 if the firm responded "yes" to the question "From 2005 to 2009 did your enterprise cooperate on any of your innovation activities with other enterprises or institutions?"; otherwise zero) (see Appendix A, Table A.1).

The independent variables must include (for econometric reasons) all the control variables from the outcome equation (1) together with at least one variable to identify equation (2).[8] This identifying variable (*Obstacle*) must influence the programme participation decision but not the innovation decision. From the theoretical perspective, factors impeding programme participation have a direct effect on the probability of treatment assignment, but have no impact on firms' innovative activities, as they are specifically associated with the selection process, not the innovation process. For this purpose, the survey included a question related only to programme participation. Whereas previous questions related directly to firms' own, particular innovation behaviour, Question 31 asked firms about SME needs in general: "What are the specific needs for SMEs to enable them to participate in innovation support programmes?" In all 18 parts of this question (see Appendix B, Table B.1), the corresponding indicator variable was defined as 1 if the response was "Very high importance" and 0 otherwise ("No importance", "Low importance", "Important" or "High importance"). Table B.1 demonstrates that most of these display widely varying proportions between participants and nonparticipants.

We constructed Equation 1 to test the hypothesis that whether or not a firm innovates depends on whether or not the firm participates in a support programme. This makes *Participation* a switching variable: according to the hypothesis, if the firm participates (*Participation* = 1) then

[7] MAPEER was a project that ran parallel to GPrix. Whereas GPrix focussed on broad innovation outcomes in traditional sector SMEs, MAPEER focussed on R&D in SMEs in general (http://mapeer-sme.eu/). The model set out in Section 3 was developed by the authors of this paper to analyse both the GPrix survey data and the MAPEER survey data.
[8] In practice, identifying variables may be desirable rather than essential. Lokshin and Sajaia (2011, p.381) report that their estimator is 'relatively robust in terms of identification of the model'.

the firm enters a state in which innovation is more likely (Regime 1); if the firm does not participate (= 0) then the firm remains in a state less conducive to innovation (Regime 0).

Because the outcome variable, *Innovation*, can exist in one of two regimes, equation 1 should be estimated over both regimes 1 and 0, in which case *Participation* disappears as a separately estimated variable. Instead of the single equation 1, we now have two equations, 1a and 1b, differentiated by an additional subscript: 1 for Regime 1 (all firms that participated in a support programme – i.e., *Participation* = 1); and 0 for Regime 0 (all firms that did not participate in a support programme – i.e., *Participation* = 0). Equation 1a estimates the probability of innovating for firms that participated in a support programme, whereas equation 1b estimates the probability of innovating for firms that did not participate in a support programme. Equations 1a and 1b, together with equation 2 are estimated simultaneously by the full information maximum likelihood estimator (Lokshin and Sajaia, 2011).

$$\begin{aligned}
&\text{Regime 1 } (Participation = 1; \text{i.e. participants}):\\
&Innovation_{i1} = \hat{C}_1 + \hat{\beta}_{11} Size_{i1} + \hat{\beta}_{21} MPower_{i1} + \hat{\beta}_{31} Export_{i1}\\
&\qquad + Industry_{I1}\hat{\phi}_{11} + \mathrm{Re}\,gion_{R1}\hat{\phi}_{21} + Country_{C1}\hat{\phi}_{31}\\
&\qquad + QFFE_{i1}\hat{\alpha}_1 + u_{i1} \qquad\qquad (1a)\\
&\text{Regime 0 } (Participation = 0; \text{i.e. nonparticipants}):\\
&Innovation_{i0} = \hat{C}_0 + \hat{\beta}_{10} Size_{i0} + \hat{\beta}_{20} MPower_{i0} + \hat{\beta}_{30} Export_{i0}\\
&\qquad + Industry_{I0}\hat{\phi}_{10} + \mathrm{Re}\,gion_{R0}\hat{\phi}_{20} + Country_{C0}\hat{\phi}_{30}\\
&\qquad + QFFE_{i0}\hat{\alpha}_0 + u_{i0} \qquad\qquad (1b)
\end{aligned}$$

This switching process is endogenous if unobserved influences on *Innovation* (u_{i1} in equation 1a and/or u_{i0} in equation 1b) are correlated with unobserved influences on *Participation* (ε_i in equation 2). In our three equation model (2, 1a and 1b), a bivariate outcome (*Innovation*) is partitioned into two regimes by a potentially endogenous bivariate switching variable (*Participation*). The three equations are linked by both common observed variables and, potentially, by common unobserved variables. The correlations between the unobservables are denoted as follows:

- between the error terms of the selection equation (ε_i) and of the outcome equation in regime 1 (u_{i1}), ρ_1 (rho1);
- between the error terms of the selection equation (ε_i) and of the outcome equation in regime 0 (u_{i0}), ρ_0 (rho0); and

- between the error terms of the two outcome regimes, ρ_{10}.

The two correlations rho1 and rho0 are particularly important, because they give insight into whether or not the selection process is endogenous. If rho1 and rho0 are both zero, then the error terms are independent across equations, which "does not allow for selection on unobservables" to be related to the innovation outcome equations (1a and 1b) (Aakvik et al., 2005, p.36). In this case, the selection process can be treated as exogenous.

The appropriate estimator for our model was developed by Aakvik et al. (2005) and has been made available as the *switch_probit* command for STATA by Lokshin and Sajaia (2011). The estimated switching probit model can be used to generate counterfactual probabilities of innovation for firms in different regimes of programme participation (Lokshin and Glinskaya, 2009, pp.489 and 503). In turn, these enable statistics to be calculated that enable the effect of programme participation to be defined and measured "in terms of impact evaluation" (Lokshin and Glinskaya, 2009, p.492). Three such statistics are of interest in the present study.

- The effect of the treatment on the treated (TT*)* statistic "estimates the effect of the programme on the entire group of people who participate in it" (Aakvik et al., 2005, p.22). In the present context, *TT* is the difference between the predicted probability of innovation for a participating firm and the probability of innovation had that firm not participated (Lokshin and Glinskaya, 2009, p.490). The average TT effect (ATT*)* is obtained by averaging TT over the subsample of participating firms (Lokshin and Glinskaya, 2009).
- The average treatment effect on the untreated (ATU) estimates the effect of a programme on the firms who did not participate (the control group) (Lokshin and Glinskaya, 2009).
- The average treatment effect (ATE) is a sample estimate of the effect of programme participation on the innovation of a firm randomly selected from the population (Aakvik et al., 2005, p.20).

3.2 THE DATA

Our population of interest is innovative or potentially innovative SMEs in traditional manufacturing industries. Resources dictated sampling from seven EU regions characterized by high employment shares in six traditional industries.[9] The sample includes 312 SMEs, comprising

[9] The firms in the sample are independent legal entities and operate as separate entities in different industries and in different countries. This satisfies the assumption of our estimator that we estimate our model on an independent, identically distributed (iid) sample (Wooldridge, 2002, p.604). For evidence that

145 participating and 167 non-participating firms. Data were gathered in 2010 from seven EU countries - the United Kingdom, Germany, Italy, Spain, Portugal, France and the Netherlands - and cover the period from 2005-2009. Detailed descriptive statistics on the survey sample are presented in Tables B.1, B.2 and B.3 (see Appendix B). The GPrix survey sample has the desired characteristics; namely: a good balance between participants and non-participants; and similar characteristics between participants and non-participants with respect to demographic and market characteristics.

The balance between total participants and non-participants is as follows: participants, 46 per cent; non-participants, 54 per cent. By country, the range is from Germany (66 per cent; 34 per cent) to the UK (34 per cent; 66 per cent) (Table B.2). Pleasingly, both participants and non-participants have similar characteristics with respect to demographics – e.g. the number of employees in 2009 and the mean number of employees in micro, small and medium- sized firms – and economic position (e.g. market power/strength of competition) (Table B.1). Conversely, as expected, there are systematic differences between participants and non-participants in all categories of innovation. Moreover, formal balancing tests – referred to in Section 4.3 below as part of our robustness checking – confirmed that most variables are balanced even before matching. In sum, the GPrix survey sampling strategy resulted in a sample well balanced between participants and non-participants with similar demographic and market characteristics. These similar characteristics are necessary for the non-participants to be a suitable comparison group.

Country dummy variables are included in the model to control for country and regional-specific firm characteristics. Table B.2 presents the number of participating and non-participating firms by country. Germany and Spain have much higher proportions of participating than non-participating firms. However, Italy, Netherlands and the UK have a smaller share of participating firms than non-participating firms, while Portugal and France have similar proportions.

Table B.3 presents data on innovative firms that have received support measures. The sample contains similar numbers of participating and non-participating firms in each category of innovation output. For each category and sub-category of innovation outcomes, both operational (product, process, organizational and marketing innovation) and economic

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the regions selected for the GPrix project represent the diversity of regional situations concerning traditional industry in the EU, see GPrix Deliverable 2.2 (2012a) http://www.gprix.eu/.

(proportions of sales attributed to new or improved products and/or processes) outcomes, the number of innovative participating firms is around half of the total number of innovative firms.

To investigate whether or not there are extreme differences in the innovation behaviour of firms between either the countries or the industries appearing in our dataset, we conducted one-way ANOVA analysis on each of the aggregate categories of operational innovation investigated in our econometric analysis.

Table 1. Tests of differences in mean percentages of firms undertaking different types of innovation (1) between countries and (2) between industries: p -values from one-way ANOVA model F-tests

	Product innovation	Process innovation	Organizational innovation	Marketing innovation
By country	0.35	0.02	0.07	0.19
By industry	0.37	0.04	0.07	0.00

Key: $p \geq 0.5$ ($p \geq 0.1$) indicates no statistically significant difference at the five per cent (one per cent) level.

Table 1 reports the p-values from the F-tests of the null that the means are the same across, respectively, countries and industries: by country there is a significant difference in firms' behaviour only in relation to process innovation; and by industry in relation to both process and marketing innovations. However, the significant country variation for process innovation is driven entirely by the Netherlands; without the Netherlands, the null of no significant difference in country means cannot be rejected (p= 0.21). Similarly, the significant industry variation in process innovation is driven by the leather industry (excluding leather, p=0.69); and in marketing innovation by the ceramics and textile industries (excluding these, p= 0.81). Overall, variation in firms' innovation behaviour varies more by industry than by country. To anticipate, this is reflected in our econometric results by the general lack of significance of country variables and by the more common significance of industry dummies.

4. RESULTS AND DISCUSSION

First, we present results from estimating our baseline model, focusing on the programme effects (Table 2). Then we report results from two major robustness checks: (1) from estimating our

GPrix Deliverable 3.3 (2012b) gives detail and examples of how the sample was obtained; see augmented model for the same 20 outcome variables (Table 3); and (2) from estimating the baseline model using Nearest Neighbour (NN) matching without replacement and with a caliper (Table 5).

4.1 BASELINE MODEL

From the perspective of evaluating the impact of publicly funded support programmes on SME innovation in traditional manufacturing industry, the most important results are the treatment effects defined in Section 3: ATE; ATT; and ATU. Of course, the validity of these post-estimation statistics depends on the validity of the regressions that are used to generate the counterfactuals from which they are calculated.

The model set out in equations 1a, 1b and 2 was estimated separately for 20 dependent variables: 16 binary variables indicating whether or not firms enacted a particular type of operational innovation (product, process, organizational and marketing innovation together with sub-categories of each); and four indicating economic outcomes (proportions of sales attributed to new or improved products and/or processes - innovative sales) (see Tables B.1 and B.3 for variable descriptions and descriptive statistics).

In each of the 20 cases, we undertook a testing down procedure to achieve parsimonious models consistent with both valid and efficient estimation. This is similar to Aakvik et al. (2005, p.26), who do not include all variables from their initial specification in their final model. Because we begin with a theoretically guided and pre-published parsimonious model, we were cautious in deleting variables. Hence, rather than simply deleting variables not estimated at conventional levels of statistical significance, we were guided by the paramount importance of the statistical validity of the model. The typical results of our testing down procedure were threefold.

1. In all 20 preferred models, two or three Question 31 variables proved to be satisfactory instruments (see Section 3 above).
2. The country dummies were typically found to be insignificant at conventional levels in the outcome equations, whereas in the selection equation only two – for Germany and Spain – were significant influences. Some insight into the reason for this can be gained by consulting Table B.1. The base (omitted) country is the UK, which has a lower proportion of participants than nonparticipants. Hence, both Germany and Spain with

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much higher proportions of participants provide a stronger contrast to the UK than do the other countries. Accordingly, in the models where the Germany and Spain dummies influence the selection process but not innovation outcomes these become additional identifying variables.

Otherwise, all variables in the parsimonious model outlined above are included in all 20 final specifications. The final specifications differ only according to variations in the identifying variables and, in the few cases where these display statistical significance, inclusion of one or two country dummies in the output equations.

Baseline models for all four aggregate categories of operational innovations are reported in full in Appendix C.[10] Each estimated model is the platform for deriving the post estimation treatment effects. For reasons of space, we do not interpret the estimated models; however, a representative model is interpreted in full in Appendix D.

For each model, the estimated coefficients are used to calculate the programme effects: ATT; ATE; and ATU. These estimated effects are presented in Table 2, columns 7-14 (following Lokshin and Sajaia, 2009 and 2011, standard errors are calculated by bootstrapping). In Table B.1, the raw or unconditional means suggest that both overall and in each separate category of innovation participating firms innovate more than do non-participating firms. Yet the estimates of ATT, ATE and ATU tell a very different story, which suggests the importance of controlling for selection (Aakvik et al., 2005).

The statistical properties of the 20 estimated models are as follows. First, columns 3 and 4 report the correlation coefficients, rho1 and rho0. In 7 from 20 cases, one of the two correlation coefficients has a value of absolute unity. In other cases, correlation coefficients are estimated imprecisely (i.e. with relatively large standard errors). Following Aakvik et al. (2005, p.37) we report the border values (1 and -1) as problematic; yet, with respect to the latter, we are “reluctant” to disregard large correlation coefficients "even if imprecisely estimated”, because this would be to disregard the potential endogeneity of the selection process. Secondly, the Wald test (reported in column 6) should reject the null of the independence of the selection and output equations. We find that in 16 from 20 cases the Wald test rejects the null of no selection bias due to unobservables at the 10 per cent level or lower (following Lokshin and Sajaia, 2011, p.379 with respect to the size of the test); the other four are not sufficiently overwhelming to

[10] A table reporting all 20 regressions in full is available upon request.

disregard the potential endogeneity of the selection process,[11] which is grounded in theory and supported by the correlation coefficients, rho1 and rho0. In sum, 13 from 20 correlation coefficients and 16 from 20 Wald tests support the validity of our estimation approach. Column 5 notes whether or not there are problems concerning the statistical validity of the estimated model in either of these respects (9 from 20 models are satisfactory in both respects).

In the results for the baseline models, the ATT effect is smaller than the ATE in almost every case (19 out of 20 models). For the ATT effect, 16 from 20 estimates are negative, of which 14 are significantly different from zero. In sum:

- ATT: the mean of the 20 values is -0.09 with a range from -0.43 to 0.53.

In contrast, for ATE 17 from 20 estimates are positive and statistically significant. In sum:

- ATE: the mean of the 20 values is 0.16 with a range from -0.11 to 0.49.

These results suggest that programme participation typically reduced the probability of innovation by programme participants by 9 percentage points but would have increased the probability for firms randomly selected from the entire population by 16 percentage points. Together these results suggest that randomly selected firms would benefit more from programme participation than do participants (Aakvik et al., 2005, p. 48). This implies that selection of SMEs into support programmes is perverse with respect to innovation outcomes (Aakvik et al., 2005, p.41).

The results for the four categories of innovative sales are somewhat different than for operational innovations. For two categories of innovative sales (more than 15 per cent and more than 25 per cent), the ATT effect is positive and statistically significant, while the dominant pattern of smaller ATT than ATE is maintained. These results might suggest that support measures have a positive effect on more innovative firms, when innovative activities are proxied by the share of sales from new product and process innovations.

The finding that the ATT effect is systematically smaller than the ATE effect is reflected in the estimates of the ATU effect (see Table 2, columns 9-11). For the ATU effect, all 20 estimates are

[11] The respective p-values are: 0.125; 0.140; 0.146 and 0.151.

positive and statistically significant. The mean of the 20 values is 0.36 with a range from 0.06 to 0.73.

To study the relationship between unobservable characteristics related to programme participation and the treatment effects, we interpret the correlation coefficients, rho1 and rho0 (Aakvik et al., 2005, pp.41-42). In 16 of the 20 models, rho1 is negative (five statistically significant at 10 per cent or less) and rho0 is positive (ten significant); in two, both rho1 and rho0 are negative; in one, both rho1 and rho0 are positive; and in one, rho1 is positive and rho0 is negative. As an example of the dominant pattern, in the model where the dependent variable is *process innovation - processes for manufacturing goods or providing services*, the correlation between the unobservables from the selection equation and the unobservables from the output equation for participants (rho1) is -0.694 (although not statistically significant), while the correlation between the unobservables from the selection equation and the output equation for non-participants (rho0) is 0.754 (and significant). The economic interpretation is as follows. The negative rho1 indicates that the unobservable characteristics of the firms participating in the support programmes are negatively correlated – although not significantly - with the innovative activities; and the positive rho0 indicates that unobservable characteristics of the non-participant firms are positively correlated with the innovative activities. In other words, firms whose unobservable characteristics suggest that they are more likely to participate in the support programme are less likely or – taking statistical significance into account – no more likely to innovate relative to a random firm from the sample; whereas firms whose unobservable characteristics suggest that they are less likely to participate in the support programme have a higher propensity to innovate. Therefore, the results suggest that the effect of support programmes on innovative activities is lower for the firms that are more likely to participate in the programmes. As Aakvik et al. (2005, p. 42) note for similar results, albeit in a different context, "selection is perverse on unobservables: treatment effects are the lowest for those most likely to participate". The implication of "perverse selection" is consistent with the characteristic contrast between a smaller ATT and a larger ATE identified above.[12]

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[12] We have estimated the treatment effects by countries and the results are consistent with our main findings. The results are available from authors upon request.

Table 2: Baseline model - programme participation effects on innovation outputs: the average treatment effect on the treated (ATT), the average treatment effect on the untreated (ATU) and the average treatment effect (ATE) (Bootstrapped standard errors, 1,000 replications)

Output dependent variable	rho1	rho0	Problem with a model?	Wald test (p value)	Average treatment effect on the treated - ATT			Average treatment effect on the untreated - ATU			Average treatment effect - ATE		
					No of obs.	Coeff.	Bootstr. SEs	No of obs.	Coeff.	Bootstr. SEs	No of obs.	Coeff.	Bootstr. SEs
Product innovation in goods	0.300 (0.422)	0.792 (0.159)	NO	0.0713	104	-0.076***	0.021	132	0.169***	0.031	236	0.061***	0.019
Product innovation in services	-1	0.846 (0.263)	rho1=-1	0.0002	96	-0.196***	0.037	123	0.542***	0.026	219	0.228***	0.018
Product innovation - combined	-0.999 (0.004)	0.871 (0.417)	NO	0.0232	108	-0.011	0.018	134	0.224***	0.025	242	0.118***	0.015
Process innovation - processes for manufacturing goods	-0.694 (1.832)	0.754 (0.305)	Wald test p=0.1252	0.1252	105	-0.046**	0.020	132	0.359***	0.021	237	0.180***	0.013
Process innovation - logistics, delivery or distribution processes	-0.197 (0.474)	0.829 (0.203)	Wald test p=0.1402	0.1402	104	-0.426***	0.027	139	0.129***	0.024	243	-0.113***	0.017
Process innovation - support processes	-0.046 (0.376)	0.957 (0.059)	NO	0.0305	108	-0.299***	0.011	141	0.057***	0.014	249	-0.097***	0.006
Process innovation – combined	-0.406 (0.588)	0.999 (0.002)	NO	0.0183	116	-0.078***	0.010	145	0.224***	0.018	261	0.084***	0.010
Organizational innovation - new business practices for organising procedures	-0.207 (0.403)	1	rho0=1	0.0147	110	-0.378***	0.016	138	0.140***	0.025	248	-0.089***	0.013

Organizational innovation - new methods of organising work responsibilities	-0.768 (0.284)	0.802 (0.195)	NO	0.0293	113	-0.398***	0.023	143	0.460***	0.018	256	0.082***	0.017
Organizational innovation - new methods of organising external relations	-0.469 (0.291)	-0.999 (0.003)	NO	0.0091	105	0.526***	0.015	131	0.458***	0.017	236	0.492***	0.010
Organizational innovation – combined	-0.642 (0.330)	0.728 (0.260)	NO	0.0488	115	-0.160***	0.013	140	0.314***	0.018	255	0.102***	0.011
Marketing innovation - changes to design or packaging	-0.566 (0.322)	0.591 (0.337)	Wald test p=0.1512	0.1512	105	-0.204***	0.025	137	0.371***	0.021	242	0.116***	0.017
Marketing innovation - new media or techniques for product promotion	-0.597 (0.345)	0.729 (0.486)	NO	0.0964	106	-0.129***	0.045	137	0.416***	0.027	243	0.176***	0.232
Marketing innovation - new methods for sales channels	-1	0.503 (0.366)	rho1=-1	0.0015	108	-0.028	0.037	135	0.694***	0.026	243	0.374***	0.021
Marketing innovation - new methods of pricing	-0.711 (0.229)	0.104 (0.628)	Wald test p=0.1463	0.1463	109	-0.062***	0.023	139	0.463***	0.017	248	0.231***	0.015
Marketing innovation – combined	-1	0.440 (0.493)	rho1=-1	0.0111	106	-0.068**	0.030	131	0.393***	0.025	237	0.195***	0.018
Innovative sales > 5 %	-0.488 (1.480)	0.805 (0.157)	NO	0.0902	113	-0.088 ***	0.015	137	0.166***	0.020	250	0.051 ***	0.011
Innovative sales > 10 %	-1	0.243 (0.833)	rho1=-1	0.0103	110	0.007	0.024	133	0.430***	0.026	243	0.240***	0.017
Innovative sales > 15 %	1	-0.130 (0.494)	rho1=-1	0.0102	109	0.113***	0.029	132	0.569***	0.022	241	0.363***	0.017
Innovative sales > 25 %	-1	-0.200 (0.813)	rho1=-1	0.0001	109	0.160***	0.025	132	0.731***	0.019	241	0.477***	0.015

4.2 AUGMENTED MODEL

The results for the augmented models presented in Table 3 show that the ATT effect is smaller than the ATE in 13 out of 19 models.[13] For the ATT effect, 17 from 19 estimates are negative, of which 15 are significantly different from zero. In sum:

- ATT: the mean of the 19 values is -0.18 with a range from -0.47 to 0.23.

In contrast, for ATE 14 from 19 estimates are positive and statistically significant. In sum:

- ATE: the mean of the 19 values is 0.10 with a range from -0.24 to 0.41.

These results suggest that programme participation typically reduced the probability of innovation by programme participants by 18 percentage points but would have increased the probability for firms randomly selected from the entire population by 10 percentage points.

Summary results for both the baseline and the augmented models are presented in Table 4. The first conclusion is a systematically smaller ATT than ATE in both models. In models without diagnostic problems, this dominant pattern is found in 8 from 9 cases in the baseline model (in 7 cases both programme effects are statistically significant); and in all 5 cases in the augmented model (in 4 cases both programme effects are statistically significant). In models with one diagnostic problem, ATT is smaller than ATE in 11 from 11 cases in the baseline model (in 9 cases both programme effects are statistically significant); and in 13 from 14 cases in the augmented model (in 9 cases both programme effects are statistically significant).

The second conclusion is only slightly less systematic, namely a negative ATT and a positive ATE. In models without diagnostic problems, this pattern is found in 7 from 9 cases in the baseline model (in 6 cases both programme effects are statistically significant); and in 5 from 5 cases in the augmented model (in 4 cases both programme effects are statistically significant). In models with one diagnostic problem, a negative ATT and a positive ATE is reported in 6 from 11 cases in the baseline model (in 5 cases both programme effects are statistically significant); and in 6 from 14 cases in the augmented model (in 5 cases both programme effects are statistically significant).

[13] We do not take into account results for the case where the output variable is product innovation - combined, as the statistical properties of the model are problematic with respect to the Wald test (p-value=0.92).

Table 3: Augmented model - programme participation effects on innovation outputs: the average treatment effect on the treated (ATT), the average treatment effect on the untreated (ATU) and the average treatment effect (ATE) (Bootstrapped standard errors, 1,000 replications)

Output dependent variable	rho1	rho0	Problem with a model?	Wald test (p value)	Average treatment effect on the treated - ATT			Average treatment effect on the untreated - ATU			Average treatment effect - ATE		
					No of obs.	Coeff.	Bootstr. SEs	No of obs.	Coeff.	Bootstr. SEs	No of obs.	Coeff.	Bootstr. SEs
Product innovation in goods	0.100 (0.488	0.764 (0.181)	NO	0.0839	104	-0.028	0.023	129	0.257***	0.028	233	0.130***	0.018
Product innovation in services	-1	0.507 (0.933	rho1=-1	0.0037	97	-0.008	0.041	121	0.551***	0.027	218	0.311***	0.024
Product innovation - combined	-0.999 (0.000)	0.300 (0.598)	Wald test p=0.9173	0.9173	108	0.127***	0.028	130	0.001	0.041	238	0.058**	0.026
Process innovation - processes for manufacturing goods	-0.400 (0.481)	1	rho0=1	0.0032	106	-0.043*	0.023	131	0.323***	0.026	237	0.153***	0.016
Process innovation - logistics, delivery or distribution processes	-0.649 (0.454)	1	rho=1	0.0031	97	-0.441***	0.035	129	0.274***	0.028	226	-0.051**	0.023
Process innovation - support processes	-0.697 (0.199)	0.598 (0.457)	NO	0.0689	100	-0.179***	0.022	129	0.324***	0.025	229	0.106***	0.021
Process innovation – combined	-0.984 (0.056)	0.990 (0.013)	NO	0.0729	116	-0.078***	0.010	142	0.251***	0.017	258	0.099***	0.012
Organizational innovation - new business practices for organising procedures	-0.477 (0.375)	1	rho=1	0.0083	107	-0.358***	0.019	131	0.123***	0.024	238	-0.093***	0.015

Organizational innovation - new methods of organising work responsibilities	-0.605 (0.268)	1	rho=1	0.0055	105	-0.436***	0.022	133	0.350***	0.023	238	-0.003	0.018
Organizational innovation - new methods of organising external relations	-0.731 (0.265)	0.665 (0.587)	NO	0.0270	105	-0.123***	0.028	128	0.553***	0.019	233	0.250***	0.018
Organizational innovation – combined	-1	0.856 (0.178)	rho1=-1	0.0065	115	-0.208***	0.021	137	0.345***	0.020	252	0.095***	0.013
Marketing innovation - changes to design or packaging	1	0.576 (0.517)	rho1=-1	0.0480	102	-0.156***	0.027	134	-0.278***	0.020	236	-0.237***	0.015
Marketing innovation - new media or techniques for product promotion	-0.700 (0.298)	1	rho0=1	0.0002	103	-0.379***	0.034	130	0.539***	0.032	233	0.124***	0.031
Marketing innovation - new methods for sales channels	-0.728 (0.312)	1	rho0=1	0.0223	105	-0.304***	0.033	128	0.538***	0.031	233	0.145***	0.026
Marketing innovation - new methods of pricing	-0.553 (0.303)	1	rho0=1	0.0096	106	-0.473***	0.029	131	0.365***	0.022	237	-0.020	0.022
Marketing innovation – combined	-1	0.742 (0.277)	rho1=-1	0.0754	109	-0.191***	0.025	134	0.456***	0.022	243	0.157***	0.020
Innovative sales > 5 %	-0.688 (0.417)	0.818 (0.237)	NO	0.0692	110	-0.087***	0.017	131	0.159***	0.019	241	0.049***	0.013
Innovative sales > 10 %	-0.231 (0.797)	1	rho0=1	0.0170	111	-0.261***	0.019	133	0.121***	0.021	244	-0.057***	0.014
Innovative sales > 15 %	-1	-0.527 (0.545)	rho1=-1	0.0011	110	0.232***	0.023	131	0.538***	0.020	241	0.409***	0.016
Innovative sales > 25 %	-1	0.080 (1.258)	rho1=-1	0.0009	110	0.007	0.025	131	0.719***	0.021	241	0.401***	0.022

Table 4: Programme effects from the baseline and augmented models: summary

Model	Number of models	Models without diagnostic problems	Models with one diagnostic problem	Models without diagnostic problems				Models with one diagnostic problem			
1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.
				ATT<ATE	ATT<ATE & both statistically significant	ATT negative & ATE positive	ATT negative & ATE positive; both statistically significant	ATT<ATE	ATT<ATE & both statistically significant	ATT negative & ATE positive	ATT negative & ATE positive; both statistically significant
Baseline	20	9	11	8	7	7	6	11	9	6	5
Augmented	19	5	14	5	4	5	4	13	9	6	5

Note: As a guide to reading Table 4, compare numbers in columns 5-8 with column 3; for example, in the Baseline Model, eight (column 5) from nine models without diagnostic problems (column 3) yield ATT<ATE. Similarly, compare columns 9-12 with column 4.

4.3. MATCHING ESTIMATION

To further check the robustness of our estimated effects, we apply Nearest Neighbour (NN) matching without replacement with a caliper of 0.25 of the standard deviation of the estimated propensity score (see Table 5).[14] We report results for the 20 baseline models. For each model we used the same specification as the respective baseline switching selection model. Balancing tests show that each variable is balanced after matching; indeed, that most variables are balanced even before matching.[15] This matching quality indicates that our sample is well balanced between treated and non-treated firms for most observed firm characteristics, which reinforces our discussion on the properties of our sample (see Section 3.2 and Table B.1.). Compared to the estimated effects reported in Tables 2 and 3, the findings from the matching estimator are skewed towards positive treatment effects; i.e. both ATT effects and ATEs are either positive or statistically insignificant. However, qualitatively the results are consistent with those reported above, insofar as across the models the ATT is systematically smaller or the same as the ATE. Finally, we applied a Rosenbaum bound approach to test for unobserved heterogeneity that can arise when unobserved firm characteristics have a significant impact on the effectiveness of innovation policy.[16] In 15 of the 20 baseline models, the test indicates that the ATT might be overestimated.[17] These findings suggest that unobserved heterogeneity should be taken into account in the impact evaluation of innovation policy and supports the application of an endogenous switching model in the present study.

[14] The choice of matching estimator reflects the consideration that the Rosenbaum bound approach can only be applied to NN matching without replacement. In order to increase the efficiency of the estimated effects, we used a caliper of the size suggested in the literature, because it removes 98 per cent of the initial bias due to covariates (Austin, 2011). We applied a range of other matching estimators with broadly similar results, which are available on request.
[15] Balancing tests include standardized differences in the sample means of participating and non-participating firms (Rosenbaum and Rubin, 1985) and the t-test of the equality of the sample means of participating and non-participating firms (see, for instance, Czarnitzki and Lopes Bento, 2013).
[16] See Rosenbaum (2002).
[17] The test cannot be conducted for the ATU or the ATE.

Table 5: Results from the Nearest Neighbour (NN) estimators - baseline model

Output dependent variable	NN without replacement and caliper of 0.25 of SD of propensity score		NN without replacement and caliper of 0.25 of SD of propensity score		Hidden bias (overestimation)
	Average treatment effect on the treated - ATT		Average treatment effect - ATE		
	Common support	Coeff. (subsampled SEs)	Common support	Coeff. (subsampled SEs)	
Product innovation in goods	230	0.222*** (0.082)	185	0.200*** (0.078)	No
Product innovation in services	220	0.167** (0.010)	176	0.193** (0.079)	Yes
Product innovation - combined	235	0.194*** (0.058)	193	0.212*** (0.058)	No
Process innovation - processes for manufacturing goods	242	0.213*** (0.079)	195	0.221*** (0.070)	No
Process innovation - logistics, delivery or distribution processes	228	0.035 (0.097)	175	0.034 (0.089)	Yes
Process innovation - support processes	236	0.000 (0.094)	188	0.037 (0.085)	Yes
Process innovation – combined	235	0.143** (0.065)	189	0.138** (0.058)	Yes
Organizational innovation - new business practices for organising procedures	235	0.035 (0.100)	179	0.017 (0.090)	Yes
Organizational innovation - new methods of organising work responsibilities	240	-0.022 (0.096)	192	0.010 (0.085)	Yes
Organizational innovation - new methods of organising external relations	237	0.231** (0.093)	188	0.250*** (0.083)	No
Organizational innovation – combined	242	0.133 (0.084)	200	0.120 (0.074)	Yes
Marketing innovation - changes to design or packaging	239	0.078 (0.080)	189	0.074 (0.085)	Yes
Marketing innovation - new media or techniques for product promotion	230	0.085 (0.094)	174	0.092 (0.085)	Yes

Marketing innovation - new methods for sales channels	244	0.237*** (0.080)	200	0.235*** (0.078)	No
Marketing innovation - new methods of pricing	244	0.021 (0.080)	198	0.056 (0.072)	Yes
Marketing innovation – combined	228	0.116 (0.086)	175	0.126 (0.081)	Yes
Innovative sales > 5 %	233	0.141** (0.076)	188	0.154** (0.071)	Yes
Innovative sales > 10 %	232	0.058 (0.094)	177	0.062 (0.078)	Yes
Innovative sales > 15 %	234	0.023 (0.095)	189	0.069 (0.081)	Yes
Innovative sales > 25 %	221	0.088 (0.089)	240	0.090 (0.079)	Yes

4.4. SUMMARY

Summary results from the switching regressions and from matching estimations are reported in Table 6. The first conclusion is that the ATT effect is systematically smaller than the ATE. For models estimated by the endogenous switching method, this finding is reported in 19 from 20 cases in the baseline model (in 16 cases both programme effects are statistically significant); and in 18 from 19 cases in the augmented model (in 13 cases both effects are statistically significant). For the baseline models estimated with the matching method, the ATT is smaller than the ATE in 13 cases (in 5 cases both effects are statistically significant).

The second conclusion arises from the somewhat less systematic finding of a negative ATT and a positive ATE. For models estimated by the endogenous switching method, this pattern is reported in 13 from 20 cases in the baseline model (in 11 cases both effects are statistically significant); and in 11 from 19 cases in the augmented model (in 9 cases both effects are statistically significant). However, results from matching are somewhat different, insofar as both ATT and ATE are positive in 12 from 20 cases (in 5 cases both effects are statistically significant). As discussed in Section 2, positively skewed programme effects estimated by matching methods are consistent with the proposition advanced by Hujer and Radic (2005) and Greene (2009) that evaluation methods that take into account only observed firm characteristics (such as matching methods) yield larger programme effects than those methods controlling further for unobserved influences.

Finally, we consider two issues concerning the validity of our estimates: first, the potential endogeneity of our *Export* variable; and, second, the sensitivity of the switching estimator to ‘model identification and the assumptions about the distribution of the error terms’ (Lokshin and Sajaia, 2011, p.379). For reasons of space, this discussion is relegated to Appendix E.

Table 6: Programme effects from the switching regressions and from matching estimators: summary

Model	Number of models	ATT<ATE	ATT<ATE & both statistically significant	ATT negative & ATE positive	ATT negative & ATE positive; both statistically significant	ATT & ATE both positive	ATT & ATE both positive; both statistically significant
Switching regression - baseline model	20	19	16	13	11	4	3
Switching regression - augmented model	19	18	13	11	9	2	1
Matching estimators - baseline model	20	13	5	1	0	12	5

5. CONCLUSIONS AND POLICY IMPLICATIONS

In this concluding section, we reprise our main findings and their policy implications. In addition, we set out some broad principles for the enactment of our policy proposals. We end with self-assessment of the main strengths and weaknesses of the study.

In the context of a population of mainly innovating SMEs, estimated programme effects consistently reveal smaller innovation effects on participating firms than could have been realized from randomly selected programme participants. Moreover, consistent with this finding of smaller ATT than ATE effects, analysis of the unobserved effects captured by our models suggests that the more likely firms are to participate in a support programme as a consequence of their unobserved characteristics the less likely they are to innovate *as a consequence*. Conversely, firms that are less likely to participate as a consequence of their unobserved characteristics would be more likely to innovate *as a consequence* (i.e. were they to participate).[18]

Our results are consistent with the hypothesis advanced in Section 2.1; namely, because of potential government failure in innovation policy, the effects of public support measures to increase private innovation may be disappointing compared to the effects typically claimed by public agencies. Yet our results also suggest a direction for policy reform to overcome government failure, thereby increasing the potential additionality of innovation support programmes. We find that cream skimming of firms on the basis of characteristics positively associated with innovation is less effective in promoting innovation than would be a strategy of randomly selecting participants. The policy implication is that ***the selection process of firms into innovation support programmes should be reformed by moving away from "cream skimming" towards random allocation.*** There is potential for improving the overall innovation outcomes of innovation support programmes for SMEs in traditional manufacturing industry by selecting typical firms with the most to gain from support rather than selecting those with the greatest propensity to innovate but the least to gain from support.[19] In other words, a more inclusive selection procedure could improve the effectiveness of innovation support programmes for SMEs in traditional manufacturing industry. Of course, some continued selection on observables (e.g. due diligence with respect to size and solvency) will still be

[18] These findings are similar to the canonical study by Aakvik et al. (2005, p.37) who also find that 'those most likely to participate in the program are those who benefit least from it'.
[19] Again, reflecting similar results, this echoes a conclusion from Aakvig et al. (2005, p.48): 'There is a potential for improving the overall employment-promoting effect of VR training by selecting those who gain the most from training rather than choosing the most employable persons.'

needed to ensure that participating firms meet eligibility requirements for participating in public support programmes.

Consistent with these proposals, the case for random allocation is gaining influence amongst policy makers. Two recent examples of successful lottery distribution of innovation vouchers are in the Netherlands and in the United Kingdom. Cornet et al. (2006) investigated the effectiveness of a Dutch innovation voucher programme for SMEs, under which vouchers were allocated by lottery. The evaluation of the programme indicates that 8 out of 10 vouchers were used to introduce innovations which, without public support, would not have been realized. This is a very large treatment effect, especially given that empirical studies, if reporting additionality at all, typically report small programme effects. Secondly, at around the time of completion of GPrix, the UK's National Endowment for Science, Technology and the Arts (NESTA) had already trialled a voucher programme with random allocation to support SME purchases of creative services. A NESTA background document to its Creative Credits voucher programme notes (NESTA, 2012 – internal, non-confidential document):[20]

> How it is decided who will receive support from all of the applications received is a major part of the programme design. Creative Credits used random allocation. This avoids 'picking winners' and making time consuming and costly subjective decisions based on the quality of proposals or applications.

Bakhshi et al. (2011) evaluated the short-term effects of the Creative Credits programme and report a high level of additionality, which quantitatively is similar to the effects of the Dutch programme discussed above. Evaluators of both voucher schemes highlight the advantages of a random distribution according to lottery:

1. to increase programme effectiveness, as argued in this paper; and
2. to "build in" evaluation by random controlled trials (RCT) and so feed back into enhanced programme effectiveness.

In addition, random allocation may lower the costs of the assignment process. However, process issues are not the topic of this paper. The following is an example - partly influenced by the findings reported in this paper – of how this recommendation may be implemented in practice.

During the dissemination stage of the GPrix project that supported the research reported in this paper, an affinity emerged between these research findings and emergent conclusions within NESTA

[20] This paragraph and the one following include references to communications and internal working documents not intended for publication. However, none of this material is confidential or in any way sensitive. If required, these e-mails and documents can be provided by the authors.

arising from their experience of innovation support: "What you have found on selection biases is consistent with … experience of business support schemes in NESTA, but I've not seen a rigorous analysis"; and "possibilities for using random assignment" (e-mail from a NESTA official to one of the authors, 24th May 2012). Indeed, we seem to have an example of similar ideas appearing at much the same time in different locations: "We've been having a discussion with the Danish Business Ministry about making use of random assignment in the Danish Vouchers Programme" (e-mail, 23-05-2012). The UK's national innovation agency, the Technology Strategy Board (TSB), is currently the main institution delivering Innovation Vouchers (£5,000 grants to stimulate innovation by "early stage, micro and small and medium businesses", TSB, 2012a – internal, non-confidential document). By mid-2012, the TSB was distinguishing between "different modes of awarding the grants", namely, through "detailed assessment or through a lottery approach" (TSB, 2012a). In turn, these alternative modes were recognized as having consequences both for administrative costs and for evaluation. Subsequently, colleagues from the GPrix project and from NESTA were invited to cooperate with the TSB to design a joint allocation and evaluation procedure. In broad outline, the resulting protocols recommended the implementation of this procedure in three stages: application; screening; and lottery.

1. The application stage includes a short, simple questionnaire to provide an integrated set of application data and baseline data for subsequent evaluation.
2. Applicants are screened for eligibility and against "due diligence" criteria according to the following principles (TSB, 2012a; original emphasis – internal, non-confidential document): "The role of the eligibility panel is ***not*** to compare projects against each other on a competitive basis, but simply to ensure that the idea qualified against the eligibility of the scheme."
3. Eligible proposals are randomly selected for support. In turn, this creates a "treatment" group (selected) and a "control" group (non-selected) for subsequent comparison and evaluation.

Development of these protocols revealed a tension between the claims of administrative feasibility and the validity of subsequent evaluation (and, therefore, its potential impact on future funding). From the perspective of evaluation, it is most important that the screening stage precedes the lottery stage. However, our experience is that administrative convenience and cost considerations incline programme managers towards the opposite. Unfortunately, screening after randomization introduces a non-random element – hence, potential bias - into the selection bias, which undermines the validity of subsequent RCT evaluation. Whereas the randomly selected proposals are categorized into eligible (participants) and ineligible (non-participants) the randomly non-selected proposals will not be screened (hence the administrative convenience and cost saving). Consequently, this procedure means that subsequent evaluation compares potentially dissimilar groups: i.e. a treatment group of eligible firms and a control group of both eligible and ineligible firms. This vitiates the benefits of random allocation for evaluation and, hence, the potential for positive feedback into programme design and effectiveness. An additional advantage of random allocation is that evaluation does not require the use of sophisticated econometric techniques, which implies that the evaluation can be conducted in a timely and cost-effectively manner (Cornet et al., 2006; Bakhshi et al., 2011).

This study has a number of novel features but also some limitations. Novel or at least unusual features include: prepublication of the model to be estimated; focus on the effectiveness of public innovation support programmes for small and medium enterprises (SMEs) in traditional manufacturing industries; and focus on output additionality in relation to both technological and non-technological innovation. Finally, the econometric method applied in the study allows for selection on both observed and unobserved firm characteristics.

There are four main limitations of the analysis. The first is inherent to all cross-section analysis; namely, inability to account fully for the cumulating of effects over time and to identify the dynamic manner in which this occurs. The GPrix survey design compensated as far as possible for this deficiency by asking firms questions to establish initial conditions for firms' current innovation activities. The second limitation is that we cannot test the distributional assumption of the estimator used in this study. However, as we argue in Appendix F, the evidence on the effects of the failure of this assumption does not undermine our main finding that estimated effects on SME participants (ATT) are systematically smaller than the estimated effects on randomly selected SMEs (ATE). The third limitation is associated with the sample size. Although our sample size is small, the sample has desirable characteristics, in particular with respect to balance between treatment and comparison groups. Moreover, our estimates typically display characteristics associated in the literature with statistical validity (namely, the Wald test for independence and the size and significance of the model correlation coefficients). The fourth limitation is that we were unable to test for partial crowding out. Although the survey questionnaire includes a question on the value of support, most participating firms did not report this amount, because respondents did not know the amount of subsidy their firms received from 2005-2009. Therefore, we are unable to utilize this variable in our econometric model. However, the absence of the amount of subsidy is a general issue in the literature on the evaluation of innovation policy (Zuniga-Vicente et al., 2012).[21] Surveys such as the Community

[21] Loss of information due to lack of data on the amount of subsidy are endemic in programme evaluation (Aakvik et al., 2005, p.26).

Innovation Survey (CIS) do not contain a question on the amount of subsidies. Even when researchers collect primary data, the response rate to questions on the amount of subsidy is very low, because respondents simply do not know the amount of subsidy, which is the case in our study.

Finally, we comment on the external validity of our findings. Edith Penrose's classic *The Theory of the Growth of the Firm* (1959, p.7), addressed a similar issue: "Many firms do not grow, and for a variety of reasons … I am not concerned with such firms, for I am only concerned with … those firms that do grow." By analogy, policy makers are concerned to encourage innovative or potentially innovative SMEs to more fully exploit their innovative potential. Correspondingly, the GPrix sample firms are overwhelmingly recent innovators (and the rest are at least sufficiently oriented towards innovation to engage with an innovation survey). As long as such firms are a priority for policy makers, then it is valid to use our results to inform policy.

Acknowledgements

This study develops analysis conducted for the 27-month GPrix project (November 2009-February 2012) commissioned by the European Commission's DG Research. Full title: Good Practices in Innovation Support Measures for SMEs: facilitating transition from the traditional to the knowledge economy. Instrument: SP4-Capacities - CSA - Support Action. Call: FP7-SME-2009-1. Grant agreement Number: 245459. DG Research funded the research but did not influence its conduct or findings. Likewise, the authors alone took the decision to prepare this article for publication. We are grateful to Bianca Buligescu at UNU-MERIT, Maastricht School of Business and Economics, for advice on our empirical strategy. In addition, discussion with Hannes Leo and other participants at the GPrix project Final Workshop in Brussels (February 28th 2012) as well as later collaboration with Hasan Bakhshi and Albert Bravo-Biosca at the UK's National Endowment for Science, Technology and the Arts (NESTA) and Hilary Chilton at the UK's Technology Strategy Board (TSB) helped to bridge the gap between policy implications/proposals and policy design/enactment. We also thank participants at the DRUID Winter Conference in Aalborg (January 2013) for feedback on an earlier version of this article.

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Appendix A:
Table A.1: Variable definition

Variable	Definition
Innovation output	DV= 1 if innovation takes place; =0 if innovation does not take place
Participation	DV=1 if the firm participated in one or more support programmes; = 0 if it did not
Size	Number of employees in 2009
MPower	DV = 1 if the firm responded “Very strong” to the question “How would you judge the competition in your main market(s)”; otherwise 0
Export	The percentage of the firm’s turnover accounted for by exports
Industry	Industry dummy variables (the omitted category is “Other”)
Country	Country dummy variables (the omitted category is the UK)
Quasi firm fixed effects (QFFE)	
Resources devoted by the firm to innovation compared to the present	DV = 1 if the response was “Fewer”; = 0 if “About the same” or “More”
The firm’s capabilities relative to other firms in their industry with respect to product innovation	DV = 1 for “Above average” and “Leading”; = 0 for “Average” and “Lagging”
The firm’s capabilities relative to other firms in their industry with respect to process innovation	DV = 1 for “Above average” and “Leading”; = 0 for “Average” and “Lagging”
The firm’s capabilities relative to other firms in their industry with respect to organizational innovation	DV = 1 for “Above average” and “Leading”; = 0 for “Average” and “Lagging”
The firm’s capabilities relative to other firms in their industry with respect to marketing innovation	DV = 1 for “Above average” and “Leading”; = 0 for “Average” and “Lagging”
Collaboration	DV =1 if the firm responded “Yes” to the question “From 2005 to 2009 did your enterprise cooperate on any of your innovation activities with other enterprises or institutions?”; otherwise 0
Obstacle	DV = 1 if the response was “Very high importance” to the question “What are the specific needs for SMEs to enable them to participate in innovation support programmes?”and 0 otherwise (“No importance”, “Low importance”, “Important” or “High importance”).

Appendix B.

Table B.1: Variable descriptions together with means and standard deviations (SD) for participants and non-participants

Variable	Variable in the dataset	Participants	Nonparticipants
Product innovation in goods	Product_innovation_goods_yes	0.83 (0.38)	0.61 (0.49)
Product innovation in services	Product_innovation_services_yes	0.58 (0.50)	0.42 (0.49)
Product innovation - combined	Product_innovation	0.93 (0.26)	0.73 (0.45)
Process innovation - processes for manufacturing goods or providing services	Q8_1_2	0.86 (0.35)	0.61 (0.49)
Process innovation - logistics, delivery or distribution processes	Q8_2_2	0.38 (0.49)	0.34 (0.48)
Process innovation - support processes (e.g. maintenance, purchasing, accounting etc.)	Q8_3_2	0.64 (0.48)	0.58 (0.50)
Process innovation - combined	Process_innovation_total	0.91 (0.29)	0.76 (0.43)
Organizational innovation - new business practices for organising procedures	Q9_1_2	0.58 (0.49)	0.48 (0.50)
Organizational innovation - new methods of organising work responsibilities and decision making	Q9_2_2	0.47 (0.50)	0.40 (0.49)
Organizational innovation - new methods of organising external relations with other firms or public institutions	Q9_3_2	0.52 (0.50)	0.29 (0.46)
Organizational innovation - combined	Organizational_innovation	0.78 (0.41)	0.63 (0.48)
Marketing innovation - changes to aesthetic design or packaging	Q10_1_2	0.47 (0.50)	0.33 (0.47)
Marketing innovation - new media or techniques for product promotion	Q10_2_2	0.47 (0.50)	0.35 (0.48)
Marketing innovation - new methods for sales channels	Q10_3_2	0.43 (0.50)	0.22 (0.42)
Marketing innovation - new methods of pricing goods or services	Q10_4_2	0.29 (0.46)	0.23 (0.42)
Marketing innovation - combined	Marketing_innovation	0.74 (0.50)	0.55 (0.50)

Innovative sales > 5 %	Q17_4	0.86 (0.34)	0.71 (0.46)
Innovative sales > 10 %	Q17_3	0.65 (0.48)	0.57 (0.50)
Innovative sales > 15 %	Q17_1	0.54 (0.50)	0.45 (0.50)
Innovative sales > 25 %	Q17_2	0.36 (0.48)	0.26 (0.44)
Any type of innovation	TOTAL	0.99 (0.08)	0.90 (0.30)
Number of employees in 2009	Q2_2009	34.56 (46.78)	34.54 (45.98)
Number of employees in micro firms (less than 10 employees)		4.73 (2.14)	4.16 (2.22)
Number of employees in small firms (less than 50 employees and more than 10)		22.51 (9.57)	23.13 (9.60)
Number of employees in medium -sized firms (less than 250 employees and more than 50)		110.23 (50.19)	104.77 (51.50)
Market power (strength of competition)	Q4t_5	0.22 (0.42)	0.25 (0.43)
Leather industry	Q3t_1	0.02 (0.15)	0.06 (0.23)
Ceramics	Q3t_2	0.10 (0.30)	0.06 (0.24)
Textiles	Q3t_3	0.10 (0.30)	0.14 (0.35)
Mechanical/Metallurgy	Q3t_4	0.34 (0.48)	0.25 (0.44)
Automotive	Q3t_5	0.09 (0.28)	0.12 (0.33)
Food products	Q3t_6	0.14 (0.35)	0.15 (0.36)
Other sectors	Q3t_7	0.20 (0.40)	0.21 (0.41)
Resources invested in innovative activities five years ago	Q12t_1	0.52 (0.50)	0.29 (0.45)
Innovative capacities for product innovation in 2005 (above average and leading)	Prodin_2005	0.31 (0.47)	0.24 (0.43)
Innovative capacities for process innovation in 2005 (above average and leading)	Procin_2005	0.27 (0.44)	0.17 (0.38)
Innovative capacities for marketing innovation in 2005 (lagging)	Q16_3t_1	0.34 (0.48)	0.35 (0.48)
Innovative capacities for organizational innovation in 2005 (lagging)	Q16_4t_1	0.27 (0.45)	0.29 (0.46)

Export	Q5_export	22.65 (30.37)	16.91 (28.58)
Collaboration [22]	Q18_yes	0.84 (0.37)	0.33 (0.47)
Administrative needs - simple application procedure (very high importance)	Q31_1t_5	0.41 (0.49)	0.32 (0.47)
Administrative needs - short time-to-contract periods (very high importance)	Q31_2t_5	0.17 (0.38)	0.16 (0.37)
Administrative needs - short application-to-funding periods (very high importance)	Q31_3t_5	0.32 (0.47)	0.21 (0.41)
Administrative needs - simple reporting requirements (very high importance)	Q31_4t_5	0.28 (0.45)	0.17 (0.37)
Administrative needs - transparent proposal evaluation procedures (very high importance)	Q31_5t_5	0.27 (0.45)	0.18 (0.37)
Administrative needs - adequate assistance/guidance during project by programme officer (very high importance)	Q31_6t_5	0.30 (0.46)	0.21 (0.41)
Financial needs - high funding rates (very high importance)	Q31_7t_5	0.23 (0.42)	0.24 (0.43)
Financial needs - limited requirements to get loans (very high importance)	Q31_8t_5	0.17 (0.38)	0.14 (0.35)
Financial needs - availability of additional financing opportunities (very high importance)	Q31_9t_5	0.15 (0.36)	0.14 (0.34)
SME (internal needs) - adequate in-house knowledge on project management (very high importance)	Q31_10t_5	0.21 (0.41)	0.12 (0.33)
SME (internal needs) - adequate networks of potential partners (very high importance)	Q31_11t_5	0.10 (0.30)	0.06 (0.23)
SME (internal needs) - compliance of programme aims to SMEs interests (very high importance)	Q31_12t_5	0.21 (0.41)	0.16 (0.36)
SME (internal needs) - strong acknowledgement of need to participate in innovation programmes (very high	Q31_13t_5	0.20 (0.40)	0.12 (0.32)

[22] Collaboration is not included in the baseline model, but is included in the augmented model. This dummy variable has a value of 1 if a firm collaborates on innovation activities with other firms or institutions.

importance)			
SME (internal needs) - easy access to information about available programmes (very high importance)	Q31_14t_5	0.24 (0.43)	0.22 (0.41)
External needs - adequate marketing of/ information about programmes (very high importance)	Q31_15t_5	0.24 (0.43)	0.17 (0.38)
External needs - adequate external assistance/guidance during project (very high importance)	Q31_16t_5	0.25 (0.43)	0.15 (0.36)
External needs - adequate external assistance/guidance after project (very high importance)	Q31_17t_5	0.17 (0.38)	0.10 (0.30)
External needs - appropriate general economic conditions (very high importance)	Q31_18t_5	0.19 (0.39)	0.20 (0.40)

Table 1 contains descriptive statistics of the variables used in the empirical analysis.[23] These are reported separately for participants and nonparticipants in support programmes for all firms in the database that satisfy the standard EU definition of SMEs (including micro enterprises). Participants are more likely to introduce innovation than nonparticipants, for all aggregate types of innovation as well as for each of the disaggregated categories. For example, for aggregate product innovation - i.e. product innovation in both goods and services - 93 per cent of participants engage in product innovation, compared to 73 per cent of the nonparticipants.

When we turn to the independent variables in the model, strikingly similar as well as different characteristics can be observed for participants and nonparticipants. Participating and non-participating SMEs have the same average number of employees. Micro and small firms also have a similar average number of employees in both categories, whereas medium-sized participating firms have, on average, 5 employees more than non-participating firms. Furthermore, non-participating firms perceive a slightly higher level of competitive pressure than do participating firms (22 per cent of participants and 25 per cent of non-participants experience “very strong” competitive pressure, which is the highest category, Q4t_5). Industries included in our sample exhibit differences with respect to firms’ participation in support programmes: leather (Q3t_1), textiles (Q3t_3), automotive (Q3t_5) and food products (Q3t_6) have a higher proportion of non-participating firms; whereas ceramics (Q3t_2) and metallurgy (Q3t_4) have a higher proportion of participating firms.

A significantly higher proportion of participating firms invested fewer resources in innovative activities in the past (Q12t_1) than they do currently (52 per cent of participants and 29 per cent of non-participants). This variable is one of five included in the model to control for initial conditions. The other four variables included in the model to control for initial conditions

[23] We have included the name of each variable as it appears in the dataset to enable the appropriate variable(s) to be identified in the dataset; hence, replication. The dataset will be made available on-line.

indicate firms' perceptions of their innovative capacities with respect to different types of innovation in 2005. For product innovation, 31 per cent of participating firms perceive their past innovative capacities as above average or leading (Prodin_2005), compared to 24 per cent of non-participating firms. For process innovation, the difference is even higher; 27 per cent of participating firms and 17 per cent of non-participating firms indicated their innovative capacities as above average or leading (Procin_2005). However, for non-technological (organizational and marketing) innovation, there is no substantial difference in past innovative capacities between those participating and non-participating firms that perceive their past capacities as lagging (Q16_3t_1 and Q16_4t_1 respectively). Considering export activities (Q5_export), participating firms are slightly more export-oriented (23 per cent) relative to non-participating firms (17 per cent). Participating firms have greater propensity to collaboration (Q18_yes) than non-participating firms (84 per cent and 33 per cent respectively).

With respect to obstacles to participating in support programmes, a higher number of participating firms indicate each category of administrative needs to be of very high importance (Q31_1t_5, Q31_2t_5, Q31_3t_5, Q31_4t_5, Q31_5t_5 and Q31_6t_5) However, almost the same proportion of participating and non-participating firms recognizes financial needs as an obstacle to participation (Q31_7t_5, Q31_8t_5 and Q31_9t_5). Further, a higher proportion of participating firms suggest that internal as well as external needs of SMEs are of very high importance (Q31_10t_5, Q31_11t_5, Q31_12t_5, Q31_13t_5, Q31_14t_5, Q31_15t_5, Q31_16t_5 and Q31_17t_5). Only for appropriate general economic conditions (Q31_18t_5) does almost the same proportion of participating and non-participating firms perceive a very high obstacle to participation.

Table B.2: Number of participating and non-participating firms by country[24]

Country	**Number of firms**	**Number of participating firms**	**Number of non-participating firms**	**Mean (standard deviation)**
Germany	38	25	13	0.66 (0.48)
Spain	53	34	19	0.64 (0.48)
Italy	46	18	28	0.39 (0.49)
Netherlands	31	12	19	0.39 (0.49)
Portugal	19	9	10	0.47 (0.51)
France	34	16	18	0.47 (0.51)
United Kingdom	91	31	60	0.34 (0.48)
TOTAL	**312**	**145**	**167**	

[24] Data in Table B.2 are for SMEs only (312 firms in total). There are 21 large firms in the sample.

Table B.3: Innovative firms that received support in each category of innovation

Variable	Number of innovative firms	Percentage of innovative firms	Number of innovative firms that received support	Percentage of innovative firms that received support
Product innovation in goods	224	67.27 %	117	52.23 %
Product innovation in services	148	44.44 %	75	50.68 %
Product innovation - combined	269	80.78 %	136	50.56 %
Process innovation - processes for manufacturing goods or providing services	234	70.27 %	124	52.99 %
Process innovation - logistics, delivery or distribution processes	107	32.13 %	59	55.14 %
Process innovation - support processes (e.g. maintenance, purchasing, accounting etc.)	190	57.06 %	87	45.79 %
Process innovation - combined	271	81.38 %	132	48.71 %
Organizational innovation - new business practices for organising procedures	171	51.35 %	85	49.71 %
Organizational innovation - new methods of organising work responsibilities and decision making	142	42.64 %	68	47.89 %
Organizational innovation - new methods of organising external relations with other firms or public institutions	124	37.24 %	75	60.48 %
Organizational innovation - combined	231	69.37 %	118	51.08 %
Marketing innovation - changes to aesthetic design or packaging	130	39.04 %	67	51.54 %
Marketing innovation - new media or techniques for product promotion	129	38.74 %	67	51.94 %
Marketing innovation - new methods for sales channels	103	30.93 %	62	60.19 %
Marketing innovation - new methods of pricing goods or services	83	24.92 %	43	46.24 %
Marketing innovation - combined	211	63.36 %	109	51.66 %
Innovative sales > 5%	246	73.87 %	127	51.63 %
Innovative sales > 10%	191	57.36 %	96	50.26 %
Innovative sales > 15%	154	46.25 %	79	51.30 %
Innovative sales > 25%	97	29.13 %	53	54.64 %

Appendix C:
Table C.1: Results for baseline model - combined categories of product and process innovations

Variable in the dataset	Product innovation - combined						Process innovation - combined					
	Participation in support programme		Non-participation in support programme		Selection decision		Participation in support programme		Non-participation in support programme		Selection decision	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Q2_2009	0.042	0.052	0.001	0.003	-0.001	0.002	0.007	0.005	0.006**	0.003	-0.001	0.002
Q4t_5	-5.164***	0.707	-0.714	0.447	-0.090	0.265	-0.115	0.419	-0.519**	0.261	0.095	0.202
Q3t_1	2.913	1.825	-0.771	0.529	0.012	0.494	7.257***	0.847	-0.665	0.511	-0.182	0.478
Q3t_2	14.541***	1.947	1.008	0.714	-0.224	0.466	0.570	0.694	0.443	0.516	0.034	0.372
Q3t_3	14.800***	1.164	0.246	0.504	-0.127	0.356	-0.079	0.553	0.392	0.417	-0.108	0.296
Q3t_4	9.223***	1.269	0.684	0.484	0.286	0.291	0.373	0.478	0.237	0.344	0.360	0.237
Q3t_5	9.852***	1.190	0.340	0.524	-0.081	0.357	0.462	0.629	0.060	0.410	-0.008	0.320
Q3t_6	12.382***	1.763	0.544	0.521	-0.553*	0.373	7.404***	0.742	0.473	0.358	-0.580*	0.328
Netherlands												
Portugal												
France												
Germany					0.721**	0.296						
Spain					1.427***	0.257					1.437***	0.267
Q12t_1	-0.623	1.301	0.877***	0.288	0.703***	0.179	-0.344	0.423	0.974***	0.250	0.688***	0.173
Prodin_2005	9.046***	0.792	1.175**	0.536	-0.173	0.254	0.159	0.439	-0.066	0.370	-0.127	0.241
Procin_2005	8.858***	0.792	-0.499	0.543	0.377	0.260	0.945*	0.525	0.511	0.380	0.400	0.253
Q16_3t_1	-0.540	1.155	-0.021	0.306	0.082	0.238	0.727	0.551	-0.190	0.308	0.075	0.219
Q16_4t_1	-4.023***	1.463	-0.549*	0.309	-0.080	0.247	-0.331	0.429	-0.334	0.286	-0.093	0.227
Q5_export	0.117 **	0.058	0.003	0.005	0.003	0.003	-0.008	0.005	-0.002	0.004	0.005*	0.003
Q18_yes												
Q31_3t_5												
Q31_7t_5												
Q31_10t_5												
Q31_17t_5					0.783 **	0.380						
Q31_18t_5					-0.332	0.281						
Log likelihood	-205.85905						-248.48591					
No of obs.	242						261					
rho1	-0.999 (0.005)						-0.406 (0.588)					
rho0	0.871 (0.417)						0.999 (0.002)					
Wald test	p = 0.0232						p=0.0183					

Table C.2: Results for baseline model - combined categories of organizational and marketing innovations

Variable in the dataset	Organizational innovation - combined						Marketing innovation - combined					
	Participation in support programme		Non-participation in support programme		Selection decision		Participation in support programme		Non-participation in support programme		Selection decision	
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff	SE	Coeff	SE	Coeff	SE
Q2_2009	0.009**	0.004	0.008**	0.004	-0.000	0.001	0.001	0.003	-0.002	0.003	-0.003	0.003
Q4t_5	-0.511*	0.289	-0.094	0.272	-0.019	0.205	-0.704**	0.329	-0.269	0.290	0.484*	0.261
Q3t_1	6.827***	0.417	-0.597	0.540	-0.1505	0.462	0.243	0.776	-0.201	0.693	0.194	0.686
Q3t_2	-0.075	0.546	1.124*	0.625	0.013	0.387	6.740***	1.825	7.238***	0.419	-0.503	0.410
Q3t_3	0.415	0.477	0.535	0.428	-0.174	0.321	7.721***	2.049	0.899*	0.465	-0.342	0.395
Q3t_4	0.185	0.370	0.276	0.340	0.494**	0.242	-0.096	0.367	0.132	0.361	0.224	0.298
Q3t_5	0.569	0.599	0.465	0.379	0.051	0.331	-0.221	0.489	-0.015	0.432	-0.246	0.386
Q3t_6	-0.230	0.387	-0.017	0.326	-0.622*	0.333		0.513	0.725	0.461	-1.054***	0.369
France												
Spain					1.464***	0.279	0.954*	0.520	-0.737	0.473	1.708***	0.311
Netherlands												
Italy												
Portugal	0.360	0.582	6.682***	0.497	-0.141	0.370						
Q12t_1	0.141	0.318	0.851***	0.270	0.725***	0.183	0.816***	0.262	0.472	0.304	0.835***	0.213
Prodin_2005							-0.473	0.365	0.723**	0.368	-0.466*	0.275
Procin_2005							0.226	0.402	-0.055	0.404	0.301	0.285
Q16_3t_1	-0.056	0.267	-0.074	0.314	-0.017	0.209	-0.783**	0.343	-0.844**	0.355	-0.081	0.270
Q16_4t_1	-0.145	0.269	-0.739**	0.328	-0.014	0.219	0.247	0.396	0.051	0.367	0.067	0.277
Q5_export	0.001	0.004	0.005	0.005	0.005	0.003	-0.001	0.005	0.004	0.006	0.004	0.004
Q31_3t_5					-0.908***	0.241						
Q31_7t_5											-0.597**	0.236
Q31_10t_5												
Q31_17t_5											0.898***	0.315
Q31_18t_5												
Log likelihood	-247.31131						-219.12568					
No of obs.	255						241					
rho1	-0.642 (0.330)						0.809 (0.187)					
rho0	0.728 (0.260)						-0.071 (0.353)					
Wald test	p = 0.0488						p=0.0651					

Appendix D: Interpretation of model estimates – example

As an example, we interpret the results for the model with the dependent variable "product innovation in both goods and services (combined)". First, the statistically significant coefficients will be discussed. In the selection equation, the coefficient on one of the variables denoting the initial conditions[25] (whether a firm devoted fewer, the same or more resources to innovation five years ago, variable Q12t_1) is statistically significant at the one per cent level. The initial conditions have a positive and significant effect on participation in support programmes; i.e. those firms which devoted more resources to innovation in 2009 than they did five years previously are more likely to participate in support programmes. As we are estimating the endogenous selection model, the model should include at least one identifying variable, i.e. the instrument. Four identifying variables are included in the model for combined product innovation: two country dummy variables, for Germany and Spain; and indicators for two parts of question 31 referring to different specific needs for SMEs in relation to programme participation (the first part indicates the importance of adequate external assistance and guidance after the support project, Q31_17t_5, and the second part indicates the importance of appropriate general economic conditions, Q31_18t_5). Both coefficients on the country DVs are statistically significant (Germany at the 5 per cent level and Spain at the 1 per cent level). Although the indicator on appropriate general economic conditions (Q31_18t_5) is statistically insignificant, it was included in the model; otherwise, the model would not converge. Finally, the indicator for adequate external assistance and guidance after the project (Q31_17t_5) has a positive and significant impact on programme participation.

In the output equation for participating firms (regime 1), high competitive pressure (Q4t_5) has a negative and significant effect on product innovation, which suggests that firms facing strong competition are less likely to introduce product innovation. Furthermore, two variables used to proxy initial conditions (i.e. innovation capabilities regarding product and process innovation, variables Prodin_2005 and Procin_2005 respectively) have a positive and significant impact on product innovation. Firms with leading innovation capabilities in the past are more likely to engage in product innovation. However, initial conditions related to organizational innovation (Q16_4t_1) have a negative effect on product innovation. Sectoral DVs (Q3t_2, Q3t_3, Q3t_4, Q3t_5 and Q3t_6) are all statistically significant, except for the leather industry (Q3t_1). Finally,

[25] Initial conditions - or quasi firm fixed effects - control for firm's innovation capacities at the beginning of the sample period.

exporting firms (Q5_export) are more likely to engage in product innovation (the coefficient is significant at the 5 per cent level).

For non-participating firms (regime 0), three variables have a significant effect on the probability of product innovation. Initial conditions related to the resources devoted to innovation (Q12t_1) have a positive and significant effect on product innovation, which indicates that development of innovation capacities increases the probability of engaging in product innovation for both participating and non-participating firms. Similar to participating firms, non-participating firms with leading innovation capabilities for product innovation in the past (Prodin_2005) are more likely to innovate. However, leading innovation capabilities in organizational innovation (Q16_4t_1) have a negative impact on product innovation, again, for both participating and non-participating firms.

Appendix E: Issues concerning the validity of our estimates

The repeated significance in the reported regressions of one or more of our five firm-level 'quasi' fixed effects (or initial conditions) is not only informative regarding the determinates of innovation but also increases confidence in the statistical validity of our estimates. There is limited scope within a cross-sectional study, particularly one analysing survey data, to address the potential endogeneity of regressors. Moreover, no estimator can address all potential specification issues. By estimating an endogenous switching model we address the main endogeneity issue in programme evaluation, that of endogenous selection (i.e. the potential endogeneity of the participation dummy). However, there may be particular concern that firms' export activities may not be exogenous with respect to innovation. If so, then endogeneity arises from omitted variables rather than simultaneity. Simultaneity assumes that causation runs directly in both directions between innovation and exports. Conversely, we argue that if exporting is potentially endogenous then this is because innovation and exports are both dependent on similar determinants, in which case they are correlated but do not cause one another. This perspective on the potential endogeneity of exports is supported by three arguments. First, in theory, exporting may be regarded as a species of innovation. This view goes back at least to Schumpeter (1942) who identified the main forms of innovation giving rise to the 'process of Creative Destruction':

> The fundamental impulse that sets and keeps the capitalist engine in motion comes from the new consumers' goods, the new methods of production or transportation, the new markets, the new forms of industrial organization that capitalist enterprise creates ... that incessantly revolutionizes the economic structure from within ...

Secondly, both case study interviews and survey data from the GPrix project suggest that SMEs in traditional manufacturing regard exporting as innovatory activity. In the GPrix survey all the examples for respondents of types of innovation followed OECD (2005), in which marketing innovation is restricted to varieties of marketing techniques but excludes entry into new markets. Yet, when asked to name the most useful innovation support measures in which they had participated, more than 10 per cent or respondents named export promotion programmes. Thirdly, in the respective literatures, models of SME innovation and of SME exporting behaviour typically have determinants in common: for example, firm size and dummies for industry and region.

In our study, we are limited in how we can address the potential endogeneity of exports. For reasons explained above, we estimate a parsimonious model and so are unable to include all possible observable influences on firms' export behaviour in the model. With panel data, we could use firm-level fixed effects to capture unobserved influences, thereby excluding them from the error term and precluding endogeneity arising from omitted variables. To mimic this approach in our cross-section model, we include, as explained above, firm-level 'quasi' fixed effects (or initial conditions) to capture otherwise unobservable firm and ownership effects. These five variables are derived from questions to firms about their innovation behaviour at the beginning of the sample period and are designed to aggregate the effects of all unobserved firm-level time invariant (or, at least, slowly moving) influences on all types of innovation, which include diversification into new markets, especially into export markets. By specifying our model to include firm-level 'quasi' fixed effects we prevent – or, at least, reduce – the presence in the error term of unobserved but systematic influences on firms' innovation, including exporting, which eliminates – or, at least, attenuates – endogeneity arising from omitted variables.

We note above that the estimation approach 'relies on an assumption of joint normality of the error terms of the estimates' (Lokshin and Sajaia, 2011, p.369). Unfortunately, there is no test for whether this assumption holds in the data. Instead, Lokshin and Sajaia (2011, p.379) undertake Monte Carlo simulations to investigate the sensitivity of their estimator to 'model identification and the assumptions about the distribution of the error terms'. Their results indicate that their estimator is 'relatively robust in terms of identification of the model'. Moreover, the authors note that this finding is consistent with Wilde (2000) who found that 'in recursive multiple-equation probit models with endogenous dummy regressors no exclusion restrictions for the exogenous variables are needed if there is sufficient variation in the data' (cited by Lokshin and Sajaia, 2011, p.381).[26] Conversely, specification where the error terms are non-normally distributed 'results in biased estimates for both ATE and ATT effects'. Moreover: 'The bias is larger for estimations based on smaller sample sizes.' However, the bias for both ATE and ATT effects is in the same direction: for a sample of similar size to the one analysed in this paper, true ATE of −0.175 is estimated at about −0.120 and true ATT of −0.336 is estimated at about −0.240; in both cases, an upward bias of about 30 per cent. In these simulations, the

[26] Monte Carlo simulations of ATE and ATT for the specification with normally distributed error terms demonstrate that: 'Even for smaller sample sizes, the method produces efficient and unbiased estimates of ATE and ATT effects' (Lokshin and Sajaia, 2011, p.381).

errors are $\chi 2$ distributed and 'simulation based on different functional forms for the non-normal distribution of the shocks … produces similar estimates' (Lokshin and Sajaia, 2011, p.381).

We may conclude for the present study that while this evidence on the effects of failure of the distributional assumption in extreme forms puts a question mark over the precise size of our estimates of ATT and ATE, it does not undermine our main finding that estimated programme effects on SME participants (ATT) are systematically smaller than the estimated effects on randomly selected SMEs (ATE). In turn, it is this finding that underpins our main policy recommendation; namely, that a more inclusive selection procedure could improve the effectiveness of innovation support programmes for SMEs in traditional manufacturing industry.

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