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10recommendations on public policy to promote SME innovation in traditional manufacturing industries

ABSTRACT

The findings of the GPrix project inform recommendations on policy and programme design to better support SME innovation in traditional manufacturing sectors. *Innovation support policies* should embrace a broad range of business activities to promote both technological and non-technological innovation. Further, policies need to balance flexibility with the need to ensure institutional stability with respect to both programmes and delivery organisations. *Innovation support programmes* are most effective when they are demand-led, timely and do not impose excessive bureaucratic demands on SME participants. In addition, programme effectiveness (i.e. additionality) could be greatly improved by reform of selection procedures, replacing the usual practice of "cherry picking" firms (i.e. picking winners) with more inclusive selection procedures (i.e. assisting a wider range of typical SMEs). Finally, we note that *an innovation tax credit consistent with a broader concept of innovation* is consistent with many of these recommendations: in particular, that public innovation support for traditional sector SMEs should be demand-led and inclusive. However, neither existing research nor the GPrix project support a general conclusion regarding the extent to which fiscal incentives should replace direct support programmes.

The GPrix project found overwhelming evidence that there is little or no best practice evaluation of innovation support programmes. In contrast to the GPrix evaluation reported in this document evaluation studies commissioned by programme managers focus on process but offer no rigorous measurement of programme effectiveness; hence, no useful guidance on additionality or value for money. For this reason, existing evaluations do not enable researchers to compare programmes or, therefore, to rank programmes or to identify a group of "best practice" programmes. Instead, the GPrix project identifies those policy and programme characteristics most conducive to promoting SME innovation in traditional manufacturing industry.

INTRODUCTION

The findings of the GPrix project inform 10 recommendations on policy and programme design to better support SME innovation in traditional manufacturing sectors. The rest of this Summary sets out these recommendations in two groups, according to whether they pertain most directly to policy design or to programme design.

- Group 1: Policy principles for the institutions, type and scope of innovation support.
- Group 2: Principles for programme design and implementation.

The policy principles draw on the entire evidence base of the GPrix project, but are informed in particular by regularities identified in the case study evidence. The programme principles likewise draw on the entire evidence base, but are most strongly informed by econometric analysis of the questionnaire survey database.

This Executive Summary sets out the 10 recommendations along with general indications of the supporting evidence. The text of the Summary is not burdened with detailed references to the evidence, which is contained in many hundreds of pages of GPrix deliverables. However, this Summary concludes with a more extended discussion of Recommendation 10: the proposal for *an innovation tax credit consistent with a broader concept of innovation*. The GPrix remit was to evaluate direct support measures. However, as a result of the GPrix Project Final Workshop (Brussels, February 28th 2012) it became apparent that many of the GPrix policy recommendations are consistent with a broadened and simplified version of existing fiscal incentives. Accordingly, on this issue, we introduce some supporting argument not presented in more detail elsewhere in Deliverable 3.3.

After the Summary, Deliverable 3.3 has two main parts that set the recommendations in the context of the underlying evidence base.

- Part 1 reports the results of econometric analysis of the survey data. The entire Study – currently in the conventional form of a Working Paper - is lengthy and of necessity rather technical. Also, it does not form part of any other deliverable. Accordingly, it is included as an Appendix to Deliverable 3.3, which will enable the validity of the analysis to be independently evaluated. Part 1 is a summary of the econometric study; it explains the methodology in non-technical terms and fully explains the policy implications supported by this analysis.
- Part 2 grounds the recommendations in the wider evidence base generated by the GPrix project, but focuses in particular on the case study evidence.

Deliverable 3.3 has two main authors, which explains stylistic differences between the Abstract, Summary and Part 1 on the one hand and Part 2 on the other.

Executive Summary Part 1:

Policy principles for the institutions, type and scope of innovation support for SMEs in traditional manufacturing industry

RECOMMENDATION 1: IMPLEMENT BEST PRACTICE EVALUATION OF PROGRAMME EFFECTIVENESS

Part 1 of Deliverable 3.3 (below) explains and documents the characteristics of best practice programme evaluation as well as the lack of best practice evaluation of innovation support programmes.[1] In brief, either innovation support programmes are not evaluated or, where they are, evaluation studies fall short of best practice. Typical practice, even when evaluation studies are commissioned, is to commission a descriptive report. Often, these are informative on the process of the programme (for example, containing evidence on what firms like/dislike about a programme). However, methodological shortcomings such as failure to use a comparison group or to address selection bias mean that existing studies are inadequate for evaluating programme effectiveness. The corollary is that existing studies are not able to measure additionality and, hence, contribute little or nothing to the assessment of value for money.

The recommendation from the GPrix project is that *best practice evaluation should be required for all major innovation support programmes*. This implies several subsidiary reforms:

1. the costs of evaluation should be built into programme budgets;
2. best practice evaluation design should inform data gathering before, during and after programme participation; and
3. training is necessary to raise the awareness of programme managers of best practice evaluation so that they can better
    a. specify requirements when commissioning evaluation and;
    b. assess the quality of subsequent evaluation reports.

To these ends,

1. best practice evaluation standards should be agreed and set out by the EU (and disseminated beyond the circles of experts already in the know), and
2. best practice evaluation should be made a condition of EU support for national/regional innovation support programmes.

In the absence of rigorous evaluation, there is no basis on which to judge programme effectiveness; i.e., there is no rigorous evidence that support programmes deliver additionality (innovation outcomes that would *not* have occurred in the absence of public support). Accordingly, there is no reliable basis for identifying best practice with respect promoting innovation. This conclusion has major implications for the GPrix policy recommendations. Although there is insufficient evidence to identify particular programmes as “best practice”, the

[1] See below: *Econometric analysis of the GPrix Survey Database: Executive Summary*, Section 2; and the appended Working Paper, *The impact of innovation support programmes on SME innovation in traditional manufacturing industries: an evaluation for seven EU regions*, Section 1.1.1.

GPrix project did generate sufficient evidence to identify principles for best practice support policy and support programmes.

RECOMMENDATION 2: ONE SIZE DOES NOT FIT ALL - MAKE INNOVATION SUPPORT CONSISTENT WITH TRADITIONAL SECTOR INNOVATION MODELS

There are different innovation models. SME innovation in traditional manufacturing industry is not based on R&D but, far more often, on the application of tacit knowledge and know-how to design – in particular, to technical design but also, in consumer goods, to aesthetic design. Correspondingly, their support needs are different from SMEs in, say, emerging technologies, where the emphasis may be on R&D and the legal protection of intellectual property. A broad innovation concept is appropriate for support programmes aimed at SMEs in traditional sectors, along the lines propounded by the *Oslo Manual*. This should embrace both technological and non-technological innovation as well as the diffusion and applications of ideas and incremental rather than radical innovation.[2] In brief, *different innovation models suggest different support programmes or, at least, a broader more inclusive emphasis in existing innovation support programmes*.

RECOMMENDATION 3: THE NEED FOR INSTITUTIONAL STABILITY.

In the UK the institutional landscape of business support is constantly changing. This contrasts with other EU partner countries, notably Germany. In this section, we refer to the UK and Germany to highlight the benefits of institutional stability in the provision of business support. In the UK, there are many programmes, which tend to be fragmented and subject to politically-driven change. Programmes are frequently dropped and new ones launched. Even when programmes have existed for sufficient time to achieve some degree of recognition among the business community they are prone to confusing name changes (e.g., from Teaching Company Scheme to Knowledge Transfer Programme). This is associated with radical changes in delivery organisations. Most recently, Regional Development Agencies (RDAs) have been abolished.

The instability of both programmes and delivery organisations in the UK causes confusion among SMEs and even trade associations, which lack the capacity to keep up with the shifting landscape of business support. The first, most direct consequence is that SMEs do not know about programmes. Indirect and possibly more serious consequences are that relationships cannot be created between business support institutions and SMEs, which contributes to a low-trust, low-information environment. Conversely, the transactions cost of gaining SME involvement in programmes is higher than it would otherwise be. In turn, this favours the perverse selection procedures of business support programmes that lower their effectiveness (i.e. reduce their additionality) (see Recommendation 8, below). The corresponding *proposal – at least for the UK - is for fewer and more stable delivery organisations and programmes*. In addition, “one-stop

[2] In line with other recent research, GPrix case studies suggest that manufacturing SMEs spend much more on design than on R&D and that technical design is the largest component of design (although this will vary from industry to industry). In turn, this is consistent with incremental rather than radical innovation.

shops” of the type introduced by Advantage West Midlands (the RDA for the West Midlands) shortly before its abolition can help to secure SME participation in business support programmes.

The need for institutional stability in innovation support programmes for SMEs in traditional sectors applies, in particular, to the UK. Of course, flexibility may be necessary to be able to introduce new programmes and delivery organisations, and/or to modify existing ones, as firms face new competitive challenges and the economy restructures. Yet evidence from the GPrix case studies suggests that the characteristic complexity and instability of UK business support constitutes a substantial barrier to SME involvement. In particular, institutional instability makes it difficult for programmes to gain reputation and for relationships to be established. Both GPrix and MAPEER case studies reveal that relationship building matters: to use quotes from MAPEER, “SMEs don’t read paperwork!” and “Personal contact – the only thing that works”. This evidence points to one explanation for the contrast between the rate of programme participation in the German sample (66%) and in the UK sample (33%) (respectively, the highest and lowest among the countries represented in the GPrix sample). Namely, the well-known stability of German business support institutions contrasts with the characteristic instability of UK business support institutions. In turn, we hypothesise that German SMEs have more and better information about support programmes, that German programmes are better able to establish reputation and, consequently, that relationships between programmes and SMEs are better formed in the German institutional environment than in the UK institutional environment (see Part 2, Section 3.1.6, below).

RECOMMENDATION 4: SUPPORT NON-TECHNOLOGICAL INNOVATION, INCLUDING MARKETING

In the GPrix case studies, many firms reported the need for assistance with marketing. Some lacked the resources to employ a marketing specialist and complained that programmes had a blinkered focus on technological innovation. The corollary is that *to promote SME innovation in traditional sectors there should be more emphasis on non-technological innovation, especially marketing*.

The GPrix team recognise that marketing support, like design support, may raise problems from the perspective of competition law. The closer support is to particular products, the more one firm may be being supported in relation to others. However, legal difficulties in definition need not be a bar to establishing principles for support programmes.

RECOMMENDATION 5: RECOGNISE EXPORTING AS INNOVATION

In the GPrix survey, respondents were asked to identify (a maximum of) their two most useful innovation support measures. Around 10 per cent responded with export promotion programmes. This was an unexpected result, because export promotion was not mentioned in the GPrix Questionnaire among the guidance notes on innovation: all the examples for respondents of types of innovation followed the *Oslo Manual* (2005) and the Community Innovation Survey, in which marketing innovation is restricted to varieties of marketing techniques but excludes entry into new markets. Hence, if anything, there was a bias against responding with these programmes.

The view that exporting may be regarded as a species of innovation goes back at least to Schumpeter (1942; emphasis added):

> 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 organisation that capitalist enterprise creates ... that incessantly revolutionises the economic structure from within...

This perspective is consistent with both case study interviews and survey data from the GPrix project, both of which suggest that SMEs in traditional manufacturing regard exporting as innovatory activity.

The corollary is that for SMEs in traditional manufacturing *exporting should be recognised as a dimension of innovation and supported as such*. In other words, innovation and export promotion should be part of a joint strategy and, hence, made available to SMEs in a related rather than in a fragmented manner. (This would facilitate, for example, joined up and timely support to enable firms to undertake changes to products and/or processes required to enter new export markets.)

We note also that one of the most commonly noted delivery organisations mentioned by UK respondents is UK Trade and Industry (UKTI), which is a long-established institution promoting UK exports and which is correspondingly well known and generally trusted by SMEs in traditional manufacturing industries. This is consistent with our emphasis on institutional stability as one of the keys to SME participation in innovation support programmes (see Recommendation 3, above).

RECOMMENDATION 6: EXTEND INNOVATION SUPPORT TO BUSINESS GROUPS

Many manufacturing enterprises belong to groups of related businesses; indeed, around 20 per cent of responses to the GPrix questionnaire are from enterprises that are legally part of larger firms while being operationally autonomous. According to GPrix case study evidence, group membership has typically been the means of enterprise survival, either by overcoming weaknesses in management or by providing a solution to the succession problem. Yet, while behaving economically as SMEs their legal status renders them ineligible for SME support programmes. The corresponding GPrix proposal is that *any company owned by a larger group but operating as a separate entity should be entitled to the same help as an independent SME*.

The GPrix team recognise the practical difficulty of distinguishing business groups from conglomerates that do not preserve the operating autonomy of constituent enterprises. Moreover, this proposal would involve a blurring of boundaries that may not be possible – or permissible – on legal grounds. Accordingly, we advance two alternative proposals to the same end:

1. either institute separate programmes for firms belonging to business groups;
2. or/and provide innovation support through tax credits that would not discriminate between firms of different sizes.

This second proposal is consistent with the GPrix proposals on R&D tax credits (see Recommendation 10, below).

RECOMMENDATION 7: INNOVATION SUPPORT PROGRAMMES SHOULD BE DEMAND LED

This principle for policy design is implicit in some of the previous recommendations: in particular, making innovation support consistent with traditional sector innovation models; supporting non-technological innovation, including marketing; and recognising exporting as innovation.

The strategic thinking behind existing innovation programmes often does not match SME needs in traditional sectors. For example, although recent reforms might help, R&D tax credits have not helped traditional-sector SMEs with innovation models based on design and/or marketing and, hence, with broad innovation needs. Conversely, *both the GPrix project and the MAPEER project found SME respondents to be overwhelmingly favourable to explicitly demand-led support programmes* such as Innovation Voucher schemes, which can be used to assess innovation potential and to scope/initiate customised projects. Alternatively, a “one stop shop” can help SMEs to avoid having to navigate the complexity of supply-driven support: SMEs take their needs to a single point of contact and are matched with the most appropriate support programme(s).

Executive Summary Part 2:

Principles for programme design and implementation

RECOMMENDATION 8: THE SELECTION PROCESS OF FIRMS INTO INNOVATION SUPPORT PROGRAMMES SHOULD BE MORE INCLUSIVE.

The GPrix survey sample is broadly representative of SMEs in the sectors under study and, by implication, of SMEs in traditional manufacturing industries in general. Within the GPrix sample, nearly all firms innovate (around 95% having undertaken activities encompassed by a broad definition of innovation within the period 2005-09). The main finding of the GPrix econometric analysis is that, in the context of a population of mainly innovating SMEs, support programmes have a zero or even slightly negative effect on the innovation of SME participants but a positive effect on randomly selected SMEs. Moreover, the more likely a firm is to participate in a support programme the less likely that firm is to innovate *as a consequence*. Conversely, firms that are less likely to participate would be more likely to innovate *as a consequence* (i.e. were they to participate).

These results are consistent with evidence from interviews with programme managers in all seven EU regions covered by the GPrix project as well as with both published and unpublished documentary sources (which were generously shared with the project team). Namely, the selection procedure adopted by programme managers is typically one of extreme “cream skimming” or “cherry picking”; in other words, firms are selected for programme participation on the basis of observed characteristics that are positively associated with innovation. The firms selected for innovation support are those most likely to innovate irrespective of programme support. The reasons for this selection strategy are two-fold, involving both incentive and scope to “cream skim”.

- The first is similar to that identified by Aakvig et al. (2000, p.45) in relation to an active labour market programme: ‘Governmental evaluations of training programs in most countries typically are based on post-program outcome measures. Such an evaluation strategy gives caseworkers an incentive to select the most employable for training.’[3]
- The second is that there are many obstacles – notably bureaucratic – to SME participation in support programmes. These are well documented by the GPrix project as well as by other projects (e.g. MAPEER). When the result of these is lack of interest by SMEs in support programmes, programme managers and case workers are forced to actively recruit which, in turn, gives more scope to “cream skim”.

Yet the consequences of a “cream skimming” selection strategy are perverse. Raw means of innovation by participants and nonparticipants will overstate the effects of participation. Indeed, the raw means may indicate positive effects where the true impact is zero or even negative. Our results suggest that cream-skimming of firms on the basis of characteristics positively associated with innovation is less effective in promoting innovation than randomly selecting participants.

These findings have direct implications for programme selection procedures. The GPrix recommendation is that *the selection process of firms into innovation support programmes should be reformed*. 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

[3] References are detailed in full in the appended econometric study: *The impact of innovation support programmes on SME innovation in traditional manufacturing industries: an evaluation for seven EU regions.*

but the least to gain from support. Of course, some transparent criteria for participation – thus some continued selection on observables - will still be needed to ensure that participating firms meet minimum thresholds for benefitting from support programmes (for example, by screening out "hobby" or "life-style" businesses). If this can be achieved then movement from cream-skimming towards a more – but not completely - inclusive selection process should enhance the effectiveness of innovation support programmes for SMEs in traditional manufacturing industries.

To reform the selection process by making it more inclusive requires many more firms to select from. Without greater awareness on the part of SMEs and correspondingly higher levels of interest, programme managers will continue to have to target and recruit firms in order to spend their programme budgets. Consequently, *a corollary of moving away from cream-skimming is the need to remove participation obstacles*; in particular, by making application, selection and reporting procedures less bureaucratic. Increasing the number of firms wanting to participate in innovation support programmes will increase the scope for reforming the selection process in favour of typical rather than special SMEs.

The GPrix survey results suggest reforms of programme procedures that will encourage participation. These are set out in the next recommendation.

RECOMMENDATION 9: MAKE IT EASIER FOR SMES TO PARTICIPATE IN SUPPORT PROGRAMMES

Question 31 on the GPrix questionnaire survey asked respondents not directly about their own experience of programme participation but for their view on SME needs in general: "What are the specific needs for SMEs to enable them to participate in innovation support programmes?" The main need identified was procedural simplicity and transparency (according to those responding with "High importance" and "Very high importance", which were the extreme categories on a five-point Likert scale).[4] Bureaucratic procedures are a barrier to entry; they impose a fixed cost on programme participation.

Also highly rated was "Short time to contract". Timeliness is hugely important: in case study interviews, SME owners and managers made the point that delay increases the risk that "another firm may get to market first". Moreover, a common theme was that the need for timeliness can be a source of tension between SMEs and Universities. Other needs noted as important were "Guidance during the project" and "Mentoring/Coaching". Regular contact with programme managers/case officers combined with mentoring/coaching could increase the effectiveness of support measures.

In brief, procedural principles for encouraging traditional sector SMEs to participate in innovation support programmes are essentially two-fold:

1. Simple and speedy procedures
    a. Reduce bureaucracy!
    b. Do quickly!
    c. Pay quickly!
2. Provide guidance during the project
    a. Mentoring
    b. Coaching

[4]Compare MAPPEER (October 2011). *Measures to foster SMEs' participation in R&D&I activities*, p.4. www.mapeer-sme.eu. This document (p.5) also described as "highly recommended" "Short time to contract periods", "Short time to funding periods" and "Short proposal evaluation periods".

Participation depends on SME awareness. In turn, SME awareness is related to the stability of programmes and of the institutions delivering them (see Recommendation 3, above). Greater institutional stability will allow relationships to be formed and, with this, the personal contacts and recommendations that can secure SME participation and commitment.

RECOMMENDATION 10: SIMPLIFY AND BROADEN THE SCOPE OF R&D TAX CREDITS

In addition, the findings of the GPrix econometric evaluation reinforce case study evidence in giving rise to the final GPrix recommendation; namely, to *simplify and broaden the scope of Research and Development (R&D) tax credits*.[5] In effect, the proposal is to transform the R&D tax credit – arguably the product of a narrow, technical model of innovation – into *an innovation tax credit consistent with a broader concept of innovation,* which includes both technological and non-technological innovation.[6]

The proposal for a broader innovation tax credit to replace or supplement R&D tax credit is consistent with other principles and recommendations supported by GPrix research into innovation and innovation support for traditional sector SMEs. First, there is the need to broaden the scope of innovation support measures to match the innovation models of SMEs in traditional sectors. In many EU countries R&D tax credits are by far the largest innovation support programme (e.g. in the UK amounting to £1 billion in 2009-10). Yet this mode of innovation support is taken up by very few SMEs in traditional manufacturing sectors. GPrix case study evidence, which is supported by GPrix survey evidence, suggests that R&D tax credits are not easily compatible with the innovation models of SMEs in traditional manufacturing industry. Few such firms have R&D departments or even undertake R&D in a sufficiently narrow sense to qualify for tax credits. Instead, their innovation models are based on design, especially technical design, as well as on tacit knowledge and advanced craft skills. Accordingly, to help SMEs in traditional sectors, R&D tax credits should be reformed in two ways:

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[5]See OECD (2011) for details on the different forms, targeting and rates of R&D tax incentives, their extent across countries and evidence that, in spite of "significant cross country differences" (p.3), the "general trend has been to increase the availability, simplicity of use and generosity of R&D tax incentives" (p.6). Of the seven regions studied by the GPrix project, six belong to countries with R&D tax incentive schemes (France, Italy, Netherlands, Portugal, Spain and the UK) and one does not (Germany currently does not provide tax incentives for R&D, although the "new German Government has agreed to introduce R&D tax credit before 2012"; OECD, 2011, p.19).

[6]These proposals are consistent with some recent developments in the practice of R&D tax credits noted by GPrix partners. Although in France and Portugal take up is still dominated by banks and large firms, in the Netherlands a wider definition has been adopted and R&D tax credits are now accessed by many SMEs. In the UK, the Small Company R&D Tax Credit is to be increased from 175% to 225% in April 2012, while accompanying changes will make it easier for SMEs to claim (indeed, the Government proclaims take-up as a key performance indicator) and the revised scheme "can help support design-led research and development" (for current changes to R&D tax credits in the UK, see: Department for Business, Innovation and Skills, December 2011, *Innovation and Research Strategy for Growth*, pp.2, 31, 44 and 89; available on-line). These observations are consistent with OECD (2011, p.18): "Some countries have also introduced fiscal measures to stimulate innovation more broadly by extending the eligible base …"

1. broaden eligibility to include innovation by design (especially technical design) and marketing activities (especially exporting); and
2. simplify application procedures to increase SME take up.[7]

Secondly, a broader innovation tax credit is consistent with promoting demand-led support (OECD, 2011, p.1):

> Tax incentives for R&D are often considered to have some advantages over direct support for R&D … They are a market based tool that aims at reducing the marginal cost to firms of R&D activities, leaving firms to decide on which R&D projects to fund.

Thirdly, if tax credits were to replace most or, at least many existing programmes then this would contribute to simplification of innovation support. In turn, long-term institutional stability would enable easier provision of advice and practical assistance, thereby increasing SME take up of innovation support (see Recommendation 3, above).[8] Moreover, if the effects of institutional stability on R&D tax credits were to apply to innovation support more broadly, then institutional stability will increase not only SME take up but also the effectiveness of innovation support (OECD, 2011, p.7):

> The stability of the R&D tax incentive over time may also play a role: expectations that R&D incentives are permanent, proxied by their stability over time, seem to strengthen the impact of the policy on R&D investment …

Fourthly, the GPrix econometric evaluation adds a value for money argument for innovation support delivered through tax credits. Compared to direct support programmes, fiscal incentives are potentially more inclusive and so potentially increase the effectiveness and, hence, the value for money of public innovation support.

> Governments face the question of which policy tools are best suited to incentivise innovation. R&D tax incentives are non-discretionary, and available to all (potential) R&D performers and therefore are industry, region and firm neutral … Grants, on the other hand, can be directed to specific projects and missions … (OECD, 2011, p.9).

Broad innovation support through the tax system will reduce the prevalence of “cherry picking” firms for support. In turn, the GPrix evaluation suggests that more inclusive selection of firms will enhance programme effectiveness (i.e. increase additionality).

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[7]The GPrix proposal for broadening the R&D tax credit into an innovation tax credit is consistent with the MAPEER recommendation to shift from the concept of “powerful research” and excellent research” to “powerful exploitation” and excellent innovation (Conference Booklet, October 2011) and the finding that “… SMEs are not attracted by the public funding (sic) research programmes.” *Measure to foster SMEs’ participation in R&D&I activities*, pp.4 and 9. www.mapeer-sme.eu

[8] Feedback from GPrix stakeholders strongly suggested that greater emphasis on fiscal incentives to promote SME innovation in traditional sectors will need to be supported by awareness raising. (Misconceptions abound: for example, many SMEs think – erroneously – that R&D needs to appear on the P&L account for them to be eligible for R&D tax credits.) In general, there is confusion among SMEs regarding who can claim and how expensive it is to do so. Events and other forms of training involving specialist Tax Inspectors would be especially useful, because owners and managers of SMEs tend not to have the time to read and digest the literature (e.g. on eligibility).

Should fiscal support replace direct support?

Given the GPrix case study evidence in favour of demand-led innovation support and the econometric evidence supporting a radical reform of programme selection procedures to make them more inclusive, participants at the GPrix Project Final Workshop in Brussels (28th February, 2012) raised the question of whether direct innovation support programmes should be replaced by fiscal incentives.

At present, R&D is typically supported by both approaches (OECD, 2011, p.3). Moreover, there is not a sufficient evidence base for concluding the superior effectiveness of the one or the other approach. OECD (2011, p.10) cites only one relevant study in this regard, for Norway, but advises that it "did not provide a ranking of policy tools according to their social returns" and that "caution should be exercised in applying the results … to other countries". Unfortunately, there is even less evidence to support such a comparison for the wider set of innovation support policies relevant to SMEs in traditional manufacturing industries. On the one hand, GPrix research has found no best practice evaluation of individual support programmes (see Recommendation 1, above); moreover, the data requirements to conduct evaluation for individual programmes far exceeded what was feasible for the GPrix project (see Part 1, Section 3 – The Data, below; and, for more detail, Part 4 of the Appended Working Paper). On the other hand, the recommended broader innovation tax credit is so far just a proposal. Accordingly, neither existing research nor the GPrix project support a general conclusion regarding the extent to which fiscal incentives should replace direct support programmes.

Reference

OECD (2011).*The international Experience with R&D Tax Incentives*. Testimony by the Organisation for Economic Cooperation and Development to the United States Senate Committee on Finance, Tuesday, September 20, 2011: Tax Reform Options: Incentives for Innovation.
http://finance.senate.gov/imo/media/doc/OECD%20SFC%20Hearing%20testimony%209%2020%2011.pdf

Part 1: Recommendations from the econometric analysis of the survey data

1. ABSTRACT

Innovation support programmes for SMEs in traditional manufacturing industries adopt a "cream-skimming" selection strategy: namely, programme managers systematically select firms on the basis of the observable characteristics most 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. We find that innovation support programmes do not increase innovation by participating firms but could be effective in promoting innovation if applied to the wider population of SMEs, most of which, at present, do not participate. The policy corollary is that the effectiveness of innovation support programmes can be improved by more inclusive selection criteria for programme participation.

The following policy implications of this investigation are discussed in detail.

1. Two recommendations arise directly from the analysis:
    a. best practice evaluation should be required for all major innovation support programmes;
    b. the selection process of firms into innovation support programmes should be reformed to be made more inclusive.
2. A further recommendation arises as a corollary: remove participation obstacles to increase the number of SMEs to select from.
3. In addition, the findings of this evaluation are consistent with another GPrix policy recommendation; namely, to simplify and broaden the scope of Research and Development (R&D) tax credits.

2. INTRODUCTION

This paper reports econometric investigation of a recent questionnaire survey designed to investigate the effectiveness of public innovation support programmes for small and medium enterprises (SMEs) in traditional manufacturing industries. This survey was conducted as part of the multi-methods GPrix project commissioned by the European Union's DG-Research.

Economic theory posits that the rationale for innovation support measures is based on overcoming a certain type of market failure; i.e. knowledge is considered as a public good, which leads to a positive externality (spillover effect). In turn, firms face difficulties in internalizing returns on innovation, and the end result is that firms will produce knowledge, embodied in innovation, under the socially optimal level (Arrow, 1962).[9] Moreover, there are other types of market failure which could induce firms to innovate less than is socially desirable, such as imperfect capital markets, high barriers to entry and exit, market power etc. (Cerulli, 2010). Yet, the effectiveness of public support might be reduced if firms substitute private investment by public funding (Hussinger, 2008). In theory, therefore, public support might enhance private investment (additionality) but besides this there is also the possibility of crowding out. In recent years, empirical analysis of the impact of public support on firms' innovative activities has been mainly concerned with providing evidence on additionality/crowding out. Furthermore, 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' innovativeness (operational innovations and innovative sales).

The central aspect of innovation policy evaluation is the issue of endogeneity. Public funding cannot be treated as exogenous, because both innovation investment and public subsidies are codetermined, i.e. government agencies choose firms not through random selection but by "cream skimming" (firms that are more innovative are more likely to receive a subsidy). The issue of endogeneity arises from both self-selection of firms (firms that are more innovative are more likely to apply for a subsidy) and the selection of firms by government agencies (firms that are more innovative are more likely to receive a subsidy).

Finally, various empirical strategies are employed in innovation policy evaluation. 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 the selection models, which we employ in our analysis, control for both selection on observables and selection on unobservables (Cerulli and Poti, 2008).

We find that innovation support programmes do not increase innovation by participating firms but could be effective in promoting innovation if applied to the wider population of SMEs, most of which, at present, do not participate. The policy corollary is that the effectiveness of innovation support programmes can be improved by more inclusive selection criteria for programme participation.

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[9] A complete list of references is to be found in the Working Paper – reporting the econometric analysis in full - appended to this deliverable.

3. EVALUATION METHODOLOGY

The *OECD Framework for the Evaluation of SME and Entrepreneurship Policies and Programmes* (2007pp.11-12) has this to say about the state of evaluation studies on SME support programmes:

> … whilst there are examples of high quality evaluations, this is not the norm … there remain too few examples of top quality evaluations … about … the impact which policy changes have upon SMEs and the economy more widely.

The methodological challenges to be confronted when evaluating innovation support programmes are explained in the OECD *Framework* (2007, pp.11 and 27; also, pp.50 and 52):

> Broadly, lower quality evaluations seem to produce more "favourable" outcomes for the project because they attribute observed change to the policy when this may not be justified … In contrast, the more sophisticated approaches strip out the other influences, and so only attribute to the programme its "real" effects … policy makers need to be aware that there is a risk that low grade evaluations … lead to misleading pictures of programme effectiveness.

To address these challenges, best practice quantitative evaluation methodology must include the following.

1. A **comparison group of non-participants**, which provides an observable "counterfactual" to the programme participants. In turn, this enables quantitative estimation of *additionality*.

2. A **selection model**, which accounts for the non-random assignment of participants and non-participants. Even in the absence of innovation support programmes, firms that would participate if they had the opportunity and firms that would not participate if they had the opportunity may have different innovation outcomes: potential participants may be the firms most inclined to innovate; conversely, these might be the least able to innovate and thus the most inclined to seek external support. Unless such effects are allowed for in the model, they are falsely attributed to programme participation. A selection model is the means to account for such potential biases in estimating programme participation effects.

4. THE DATA

In principle, the GPrix survey required a random sample from the population of SMEs in the six targeted traditional manufacturing sectors in the seven regions covered by the project. The practical difficulty to be confronted was the anticipation – arising from previous experience as well as the literature on survey responses - that it would be difficult to obtain large numbers of questionnaire responses from SMEs in traditional sectors. For this reason, each partner accepted a target of 100 responses which, in the event, was achieved only in the West Midlands.

A simple representative sample of all manufacturing SMEs in the traditional sectors of interest would include *insufficient programme participants for useful analysis*. Accordingly, the GPrix project used a species of stratified sampling; i.e. a random sample biased in a deliberate way towards programme participants. For concreteness, we refer to the West Midland; however, all partners proceeded in a similar manner. The challenge was to generate a sample of SMEs in five target sectors of traditional manufacturing with a high proportion of programme participants. To this end, a two-fold approach was implemented:

1. to generate a sample of SMEs in five target sectors of traditional manufacturing to be representative in all respects *except* for programme participation; and
2. to ensure a sufficient number of programme participants to be able to address the issue of interest (i.e. programme effectiveness) the sample was deliberately biased to over-represent participants in support programmes.

In addition, we provided an "incentive" for all respondents (a prize draw for one of five £100 vouchers for either a top-class restaurant or a department store). The 98 completed questionnaires returned give an overall response rate in the West Midlands of around 2½ percent. The other GPrix partners implemented a similar approach, which was arrived at by sharing experiences during the first year of the project. In total, completed responses were received from 333 firms in the target regions in 7 countries.

Detailed descriptive statistics on the survey sample are presented in Tables 1, 2 and 3 in the full report (the Working Paper appended to this deliverable). 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 except for innovation behaviour.

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%; 34%) to the UK (34%; 66%) (see Table 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 firms – and economic position (e.g. market power/strength of competition) (see Table 1). Conversely, as expected, there are systematic differences between participants and non-participants in all categories of innovation. Participants are more likely to introduce innovation than nonparticipants, for all aggregate types of innovation as well as for each of the disaggregated categories. 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. Yet, differences with respect to innovation behaviour suggest that the analysis must control for selection bias. Accordingly, our modelling strategy is designed to identify additionality – i.e. the effects of programme participation on innovation outcomes over and above differences accounted for by observed and unobserved differences between participants and non-participants.

5. ESTIMATION

We test the hypothesis that whether or not a firm innovates depends on whether or not the firm participates in a support programme.

Our sample of both “treated” (participating) and “comparison” (nonparticipating) firms enables the effect of programme participation to be defined and measured in terms of two statistics: the average treatment effect (*ATE*); and the average effect of treatment on the treated (*ATT*).

- In the context of our model, the *ATE* is a sample estimate of the effect of programme participation on the innovation of a firm randomly selected from the population. With binary outcomes, the *ATE* is the probability of a firm innovating when participating minus the probability of that firm innovating when not participating in a programme

- The *TT* statistic estimates the effect of a programme on the entire group of firms who participate in it. The average treatment effect on participants (*ATT*) is obtained by averaging *TT* over the subsample of participating firms.

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, ATE and ATT.

Our model was estimated separately for 20 dependent variables; 16 binary variables indicating whether or not firms enacted a particular type of "operational" innovation (product, process, organisational 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) (see Tables 1 and 3 for variable descriptions and descriptive statistics).

6. RESULTS

In Table 1 in the full report (Working Paper), the raw or unconditional means suggest that both overall and in each separate category of innovation participating firms innovate more than nonparticipating firms. Yet the estimates of ATT and ATE tell a very different story, which suggests the importance of controlling for selection (Aakvik, 2000, p.33).

If we first look at the results for the models where the dependent variables are different types of operational innovation (product, process, organisational and marketing innovations), the ATT effect is smaller than the ATE in almost every case (15 out of 16 models). For ATT 10 from 16 estimates are negative, of which 8 are significantly different from zero. In sum:

- ATT: the mean of the 16 values is -0.06 with a range from -0.43 to 0.27.

In contrast, for ATE 12 from 16 estimates are positive and statistically significant. In sum:

- ATE: the mean of the 16 values is 0.12 with a range from -0.17 to 0.37.

These results suggest that programme participation typically reduced the probability of innovation by programme participants by 6 percentage points but would have increased the probability for firms randomly selected from the entire population by 12 percentage points. Together these results suggest that randomly selected firms benefit more from programme participation than do participants. This implies that selection of SMEs into support programmes is perverse with respect to innovation outcomes.

When the results from the four additional model specifications for categories of innovative sales are included in our review, the results from the models with operational innovation outputs are reinforced. The ATT effect is smaller than the ATE in 18 out of 20 models, with a probability of this result having occurred without a systematic relationship of 0.0002. The results strongly suggest that the effect of support programmes would be more profound if firms were to be randomly chosen to participate in the programmes. Furthermore, a high proportion of the models (9 out of 20) yield a zero or negative ATT and a positive ATE, with a probability of this result having occurred without a systematic relationship of 0.03. These results indicate that on average the impact of support measures on innovation output in the participating firms is at best zero, while the support programmes could have had a positive overall effect on innovation output had the firms been randomly chosen.

The ATT and ATE effects by country are presented in Tables 5 and 6. The overall conclusion is that neither the ATT nor the ATE effects change signs if we compare ATT/ATE across the sample with the individual effects for each country. However, the magnitude and in a few cases the sign of the two effects do differ across countries.

7. CONCLUSIONS AND POLICY IMPLICATIONS

In the absence of randomised experiments to evaluate innovation support for SMEs in traditional manufacturing industries, to identify the effect of programme participation requires not only a comparison group to control for innovation by non-participants but also a model to estimate the effects of programme participation beyond the effects of selection bias. These best practice requirements are demonstrated by the contrast between the raw descriptive statistics for innovation by participants and nonparticipants and the estimated treatment effects discussed in the previous section.

In our study, the gross effects are most misleading if interpreted as indicating causal effects of programme participation on firms’ innovation behaviour. In the context of a population of mainly innovating SMEs, our estimated programme effects – ATT and ATE - suggest that support programmes have a zero or even slightly negative effect on the innovation of SME participants but a positive effect on randomly selected SMEs. Moreover, consistent with this finding, analysis of the unobserved effects captured by our model suggest that the more likely a firm is to participate in a support programme the less likely that firm is to innovate *as a consequence*. Conversely, firms that are less likely to participate would be more likely to innovate *as a consequence* (i.e. were they to participate). In relation to the wider literature on programme effects, the evidence of the estimated ATT effects reported in this study is consistent with those previous investigations that find no evidence of additionality or even of a small crowding out effect.

These results are consistent with evidence from interviews with programme managers in all seven EU regions covered by the GPrix project as well as with both published and unpublished documentary sources (which were generously shared with the project team). Namely, the selection procedure adopted by programme managers is typically one of extreme “cream skimming” or “cherry picking”; in other words, firms are selected for programme participation on the basis of observed characteristics that are positively associated with innovation. The firms selected for innovation support are those most likely to innovate irrespective of programme support. The reasons for this selection strategy are two-fold, involving both incentive and scope to "cream skim".

- The first is similar to that identified by Aakvig et al. (2000, p.45) in relation to an active labour market programme: 'Governmental evaluations of training programs in most countries typically are based on post-program outcome measures. Such an evaluation strategy gives caseworkers an incentive to select the most employable for training.'
- The second is that there are many obstacles – notably bureaucratic – to SME participation in support programmes. These are well documented by the GPrix project as well as by other projects. When the result of these is lack of interest by SMEs in support programmes, programme managers and case workers are forced to actively recruit which, in turn, gives more scope to "cream skim".

Yet the consequences of a "cream skimming" selection strategy are perverse. Raw means of innovation by participants and nonparticipants will overstate the effects of participation. Indeed, the raw means may indicate positive effects where the true impact is zero or even negative. Our results suggest that cream-skimming of firms on the basis of characteristics positively associated with innovation is less effective in promoting innovation than randomly selecting participants (Aakvig et al., 2000, pp.44-45).

These findings have direct implications for policy makers.

1. ***Best practice evaluation should be required for all major innovation support programmes***. As Aakvik et al. (2000, p.45) note in relation to training programmes: "Caseworkers are seldom able to estimate treatment effects. Thus guidance on who should participate should be based on results from research rather than by rules-of-thumb." Even where consultants are engaged to evaluate programmes, the evidence from the GPrix research is that evaluation is never conducted according to best practice guidelines. Sometimes, this is the fault of consultants who either do not know of best practice or, when they do, ignore it. Conversely, when consultants suggest best practice evaluation – in particular, the use of a comparison group – lack of knowledge on the part of programme managers can make them disinclined to incur the expense of sound evaluation. Accordingly, while endorsing the general advice of Aakvik (2000), to spread best practice evaluation, to do so will require several more supporting reforms:
    a. the cost of evaluation should be built into programme budgets;
    b. evaluation design should inform data gathering before, during and after programme participation; and
    c. training should be required to raise the awareness of programme managers of best practice evaluation so that they can better specify requirements when commissioning evaluation and assess the quality of subsequent evaluation reports.

2. ***The selection process of firms into innovation support programmes should be reformed***. 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. Of course, some transparent criteria for participation – thus some continued selection on observables - will still be needed to ensure that participating firms meet minimum thresholds for benefitting from support programmes (for example, by screening out "hobby" or "life-style" businesses). If this can be achieved then movement from cream-skimming towards a more – but not completely - inclusive selection process should enhance the effectiveness of innovation support programmes for SMEs in traditional manufacturing industries.

3. To reform the selection process by making it more inclusive requires many more firms to select from. Without greater awareness on the part of SMEs and correspondingly higher levels of interest, programme managers will continue to have to target and recruit firms in order to spend their programme budgets. Consequently, ***a corollary of moving away from cream-skimming is the need to remove participation obstacles***; in particular, by making application, selection and reporting procedures less bureaucratic. Increasing the number of firms wanting to participate in innovation support programmes will increase the scope for reforming the selection process in favour of typical rather than special SMEs.

In addition, the findings of this evaluation are consistent with another GPrix policy recommendation; namely, to ***simplify and broaden the scope of Research and Development (R&D) tax credits***. Greater emphasis on innovation support through the tax system will reduce the prevalence of "cherry picking" firms for support. In turn, the GPrix evaluation suggests that by supporting all eligible firms, programme effectiveness will be enhanced (i.e. additionality increased).

In many EU countries R&D tax credits are by far the largest innovation support programme (e.g. in the UK amounting to £1 billion in 2009-10). Yet R&D tax credits are not easily compatible with the innovation models of SMEs in traditional manufacturing industry. Both the GPrix questionnaire survey and the GPrix case studies support other research in finding that few such firms have R&D departments or even undertake R&D in a sufficiently narrow sense to qualify for tax credits. Instead, their innovation models are based on design, especially technical design, as well as on tacit knowledge and advanced craft skills. Accordingly, to help SMEs in traditional sectors, R&D tax credits should be reformed in two ways:

1. broaden eligibility to include innovation by design (especially technical design) and marketing activities (especially exporting); and
2. simplify application procedures to increase SME take up.

In effect, the proposal is to transform the R&D tax credit – arguably the product of a technical and narrow model of innovation – into ***an innovation tax credit consistent with a broader concept of innovation,*** which includes both technological and non-technological innovation.

The proposal for a broader innovation tax credit to replace or supplement R&D tax credit is consistent with other principles and recommendations supported by GPrix research into innovation and innovation support for traditional sector SMEs. In brief, these are as follows.

1. Broaden the scope of innovation support measures to match the innovation models of SMEs in traditional sectors.
2. Favour demand-led support which, in turn, has the advantage of being market-led rather than bureaucratically-led.
3. Simplify innovation support for SMEs; fund fewer and more stable programmes. In turn, reducing the number of support programmes is more likely to increase take-up by SMEs if two further GPrix recommendations were to be implemented:
    a. long-term institutional stability of the innovation tax credit, facilitating recognition, trust and investment in the fixed costs of application; and
    b. advice and practical assistance in making applications, especially for first-time applicants.
4. An innovation tax credit would end discrimination against enterprises that belong to groups and so, although operating much like SMEs in an economic sense, do not satisfy legal definitions for participation in many SME support programmes.

Finally, to these principles and recommendations the GPrix evaluation adds a value for money argument for innovation support delivered through tax credits. Broad innovation support through the tax system will reduce the prevalence of "cherry picking" firms for support. In turn, the GPrix evaluation suggests that more inclusive selection of firms will enhance programme effectiveness (i.e. increase additionality).

Part 2: Recommendations from the wider evidence base

Del.3.1 >>Draft recommendations report<<displays a collection of issues to be addressed by policy makers and programme makers of innovation support measures. These mirror the results of the analysis of documents, survey data, interviews, case studies and associated best practices. The presented recommendations on the design and implementation of support policies as well as support programmes, might be considered as guidelines to improve existing initiatives and to develop future measures.

1 RECOMMENDATIONS ON THE DESIGN AND IMPLEMENTATION OF SUPPORT POLICIES

1.1 BROADENING THE UNDERSTANDING OF INNOVATION

Secondary types of innovation– marketing and organizational innovation (or non-technological innovation) are underrepresented among the innovation initiatives. However, enterprises often choose to use specific support measures for product and process innovation (technological innovation), as they are likely to be financially more attractive. Figure 1 presents the main types of innovation among the GPrix case study SMEs; and Figure 2 presents the types of innovation support measures that they used.

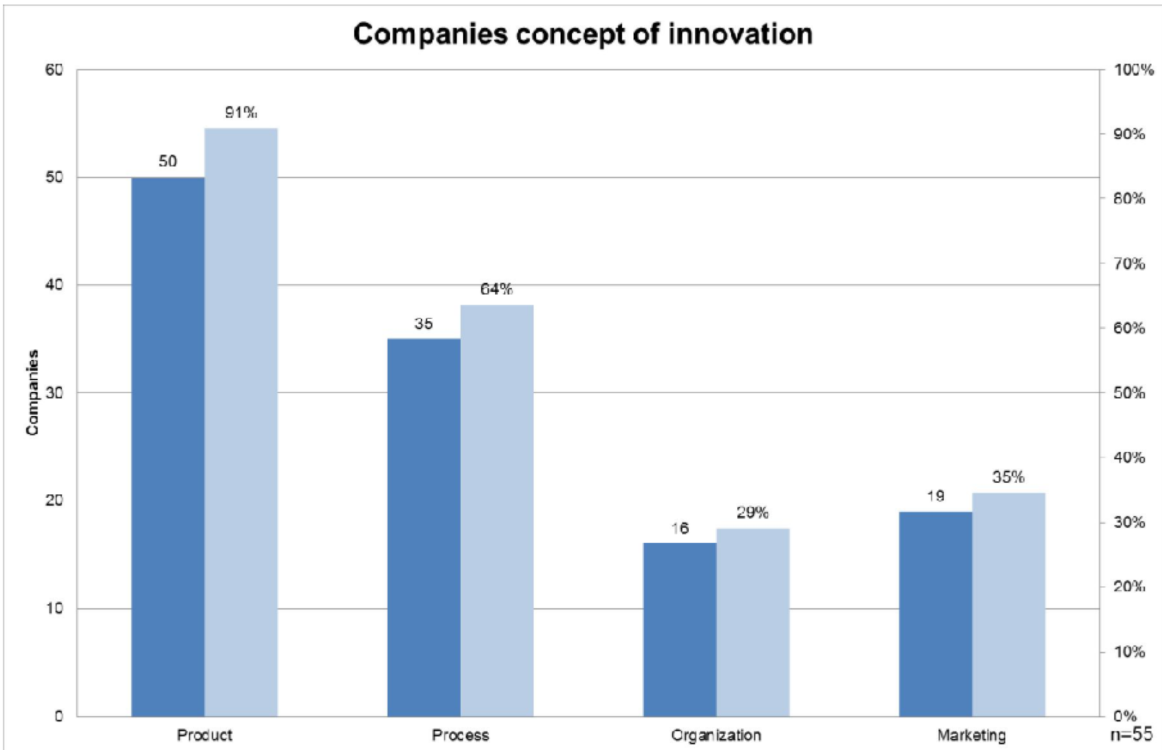

Figure 1: Diversification of innovation initiatives among companies[10]

[10]GPrix Consortium, Del1.7, p. 21.

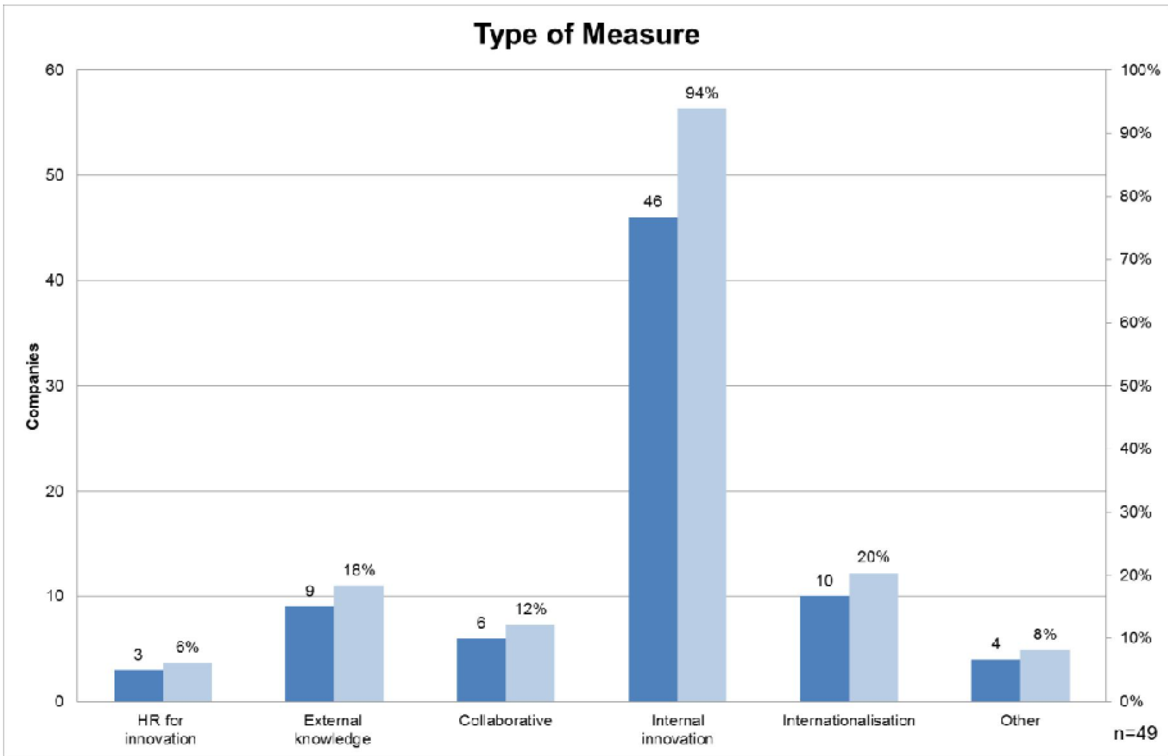

Figure 2: Focus of measures chosen[11]

According to the numbers shown above, one can see the large share of non-technological innovation. This reveals the necessity of supporting innovation in a broader sense and developing a more diverse perspective in accord with the innovation models of SMEs in traditional manufacturing industries. Policy makers thus have the task to foster a broader understanding of innovation by a variety of means.

Conversely, policy makers need to sensitize enterprises to the full spectrum of innovation, by organizing and realizing dedicated marketing actions, such as information events or workshops on innovation management, promoting diverse types of innovation and approaches to support measures and services. By doing so, companies are likely to become interested in innovation initiatives and might more readily apply for a support measure.

Either developing dedicated innovation support measures for product, process, marketing and organizational innovation or broadening existing narrowly-focussed support measures could be approaches to increase the overall participation of traditional sector SMEs and, furthermore, to foster applications and implementations of non-technological innovation initiatives.

1.2 TRANSPARENCY AND STABILITY OF THE INNOVATION SUPPORT LANDSCAPE

As the descriptions of numerous innovation support programmes, presented in Del.1.5, show, the innovation landscape in Europe is vast, diverse and almost unmanageable. In every member state there are support programmes available on the regional, national and European

[11] GPrix Consortium, Del1.7, p. 21.

levels.[12]The GPrix consortium initially focused on regional level, but soon realized that SMEs do not distinguish between the different levels. SME are often unable to give even the correct name of the specific support programme they had received. Within the survey there were a lot of incorrect programme names from the different levels (regional, national, European).

In each of the 7 partner regions, companies have difficulties over viewing recent developments within the field of innovation. Numbers, names, division and relationships of support programmes change constantly, which leads to confusion, foot-dragging and mistrust among interested parties. Table 1 gives an overview of the 32 innovation support programmes undertaken by the GPrix case study SMEs.

Country (Region)	Analysed Programmes
France (Limousin)	7
Germany (Saxony-Anhalt)	6
Italy (Emilia-Romagna)	4
Netherlands (North Brabant)	4
Portugal (Northern / Central Portugal)	3
Spain (Comunidad Valencia)	4
United Kingdom (West Midlands)	4

Table 1: Overview of analysed innovation support programmes in the 7 GPrix regions[13]

To avoid this barrier to participation, the vast area of innovation support programmes needs a well-arranged structure to overcome the characteristic traditional sector SME scepticism and lack of participation. It is thinkable that the landscape could be restructured into target-oriented support programmes, which automatically supports an attractive stability.

In the UK the institutional landscape of business support is constantly changing. This contrasts with other EU partner countries, notably Germany. In this section, we refer to the UK and Germany to highlight the benefits of institutional stability in the provision of business support. In the UK, there are many programmes, which tend to be fragmented and subject to politically-driven change. Programmes are frequently dropped and new ones launched. Even when programmes have existed for sufficient time to achieve some degree of recognition among the business community they are prone to confusing name changes (e.g., from Teaching Company Scheme to Knowledge Transfer Programme). This is associated with radical changes in delivery organisations. Most recently, Regional Development Agencies (RDAs) have been abolished.

The instability of both programmes and delivery organisations in the UK causes confusion among SMEs and even trade associations, which lack the capacity to keep up with the shifting landscape of business support. The first, most direct consequence is that SMEs do not know about programmes. Indirect and possibly more serious consequences are that relationships cannot be created between business support institutions and SMEs, which contributes to a low-trust, low-information environment. Conversely, the transactions cost of gaining SME involvement in programmes is higher than it would otherwise be. In turn, this favours the perverse selection procedures of business support programmes that lower their effectiveness (i.e. reduce their additionality) (see Recommendation 8 in the Executive Summary). The corresponding *proposal – at least for the UK - is for fewer and more stable delivery organisations and programmes*. In

[12]As an example: You can find 33 national support programmes (grants) in Germany dedicated to businesses (See http://erawatch.jrc.ec.europa.eu/erawatch/opencms/search/)

[13] See GPrix Consortium, Del1.5.

addition, “one-stop shops” of the type introduced by Advantage West Midlands (the RDA for the West Midlands) shortly before its abolition can help to secure SME participation in business support programmes.

The need for institutional stability in innovation support programmes for SMEs in traditional sectors applies, in particular, to the UK. Of course, flexibility may be necessary to be able to introduce new programmes and delivery organisations, and/or to modify existing ones, as firms face new competitive challenges and the economy restructures. Yet evidence from the GPrix case studies suggests that the characteristic complexity and instability of UK business support constitutes a substantial barrier to SME involvement. In particular, institutional instability makes it difficult for programmes to gain reputation and for relationships to be established. Both GPrix and MAPEER case studies reveal that relationship building matters: to use quotes from MAPEER, “SMEs don’t read paperwork!”; and “Personal contact – the only thing that works”. This evidence points to one explanation for the contrast between the rate of programme participation in the German sample (66%) and in the UK sample (33%) (respectively, the highest and lowest among the countries represented in the GPrix sample). Namely, the well-known stability of German business support institutions contrasts with the characteristic instability of UK business support institutions. In turn, we hypothesise that German SMEs have more and better information about support programmes, that German programmes are better able to establish reputation and, consequently, that relationships between programmes and SMEs are better formed in the German institutional environment than in the UK institutional environment (see Section 3.1.6, below).

1.3 EXPANSION OF TARGET GROUPS; IN PARTICULAR, TO INCLUDE BUSINESS GROUPS

The GPrix case study SMEs included both participants and non-participants in innovation support programmes and, as displayed in Figure 3, are mostly SMEs and micro enterprises.[14]

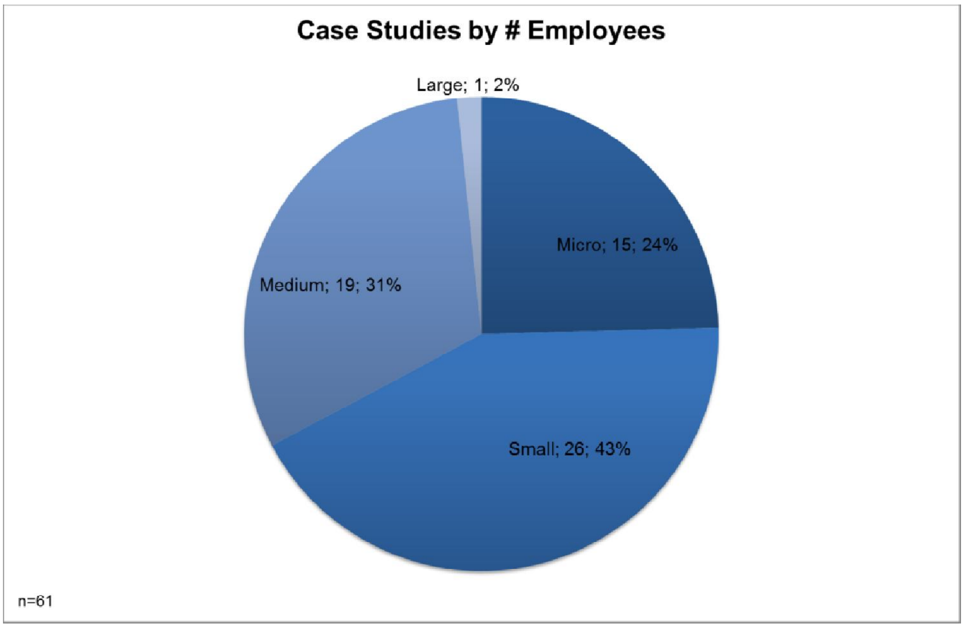

Figure 3: Distribution of business types in the GPrix case study SMEs[15]

[14] See GPrix Consortium, Del1.5.

By participating in innovation support measures, the case study enterprises reported that they had been able to boost their innovation activities and related efforts, such as job creation and export, etc., as Figure 4 shows.

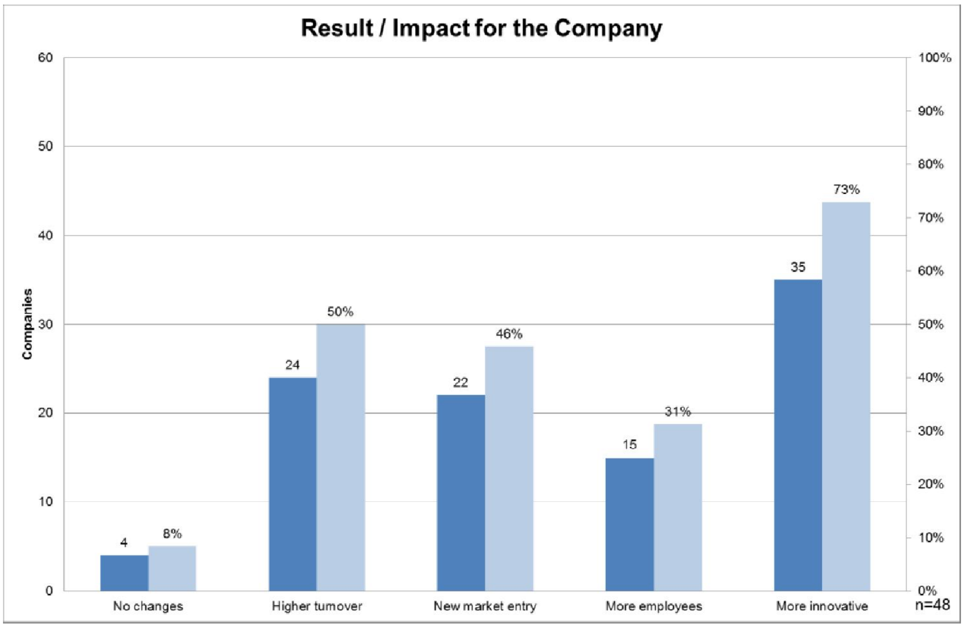

Figure 4: Impact of innovation support measures[16]

According to Figure 4, enterprises definitely profit by participating in innovation support measures. Nevertheless, until today, the majority of analyzed programmes aim at SMEs conforming to the actual EU definition – some of them even restricted to the region. Yet smaller enterprises and also SMEs belonging to business groups face the same challenges of restricted resources for innovation initiatives, and are thus in need of financial support by participating in relevant programmes.

Many manufacturing enterprises belong to groups of related businesses; indeed, around 20 per cent of the total responses to the GPrix questionnaire are from enterprises that are legally part of larger firms while being operationally autonomous. According to GPrix case study evidence, group membership has typically been the means of enterprise survival, either by overcoming weaknesses in management or by providing a solution to the succession problem. Yet, while behaving economically as SMEs their legal status renders them ineligible for SME support programmes. The corresponding GPrix proposal is that *any company owned by a larger group but operating as a separate entity should be entitled to the same help as an independent SME*.

Within the traditional sectors we see a lot of SME-alike companies belonging to bigger groups. Within a bigger group SMEs can share synergetic effects (e.g. in procurement or marketing) or even ensure their survival as losses can be compensated. Thus the GPrix consortium recommends policy makers to distinguish between two groups of SMEs in traditional manufacturing sectors:

1. Dependent SMEs belonging to a group; and

[15]GPrix Consortium, Del1.7, p. 13.

[16]GPrix Consortium, Del1.7, p. 38.

2. Independently acting SMEs belonging to a group.

Independently acting SMEs that belong to a group but do not fit the EU SME criteria are characterized by the GPrix consortium as following:

1. Less than 250 employees and
2. Less than 50 million Euro annual turnover or less than 43 million Euro balance sheet total and
3. Own products or services independent from group product portfolio (not produced / sold by other associate company) and
4. Own sales responsibilities and
5. Own innovation activities independent from the group (e.g. R&D department, own new market strategy and market entry).

Conversely a SME operating as an “elongated workbench” (just a production facility) would count as belonging to the first mentioned SME type, which is not the focus of the GPrix recommendation. However, independently operating SMEs (belonging to a group) should be treated by programme managers as eligible SMEs from our point of view - at least in the traditional sector. As the challenges facing the interviewed independent SMEs – whether they belong to a group or not – are the same and all use innovation support programmes as a financial resource, they should all have access to innovation support initiatives.

In addition, to inform target groups about recent possibilities to apply for innovation support measures, potential applicants should be approached directly. Dedicated marketing actions on a regional and national level are likely to increase the general awareness of available support as well as to raise awareness among certain underrepresented target groups.

The effectiveness of support measures: a note on the apparent inconsistency between the case study evidence and the econometric evidence.

Figure 4 (above), from the case study evidence, suggests overwhelmingly positive outcomes from innovation support measures. In contrast, our econometric analysis of the survey evidence finds the typical effect of support measures to be negligible (see Part 1, Recommendation 8, above; and, for a detailed explanation, Section 6 – Results and Discussion – of the appended Working Paper).

Our explanation of this apparent inconsistency is that firms agree to participate in case studies as a result of a self-selection process: overwhelmingly, firms that participate want to proclaim a success; while, on occasion, a firm might agree to a case study to complain about a programme failure, the experience of the GPrix team is that this is much less common. Consequently, the case study evidence is overwhelmingly positive. In contrast, the survey database includes a comparison group of non-participants which, in turn, enables the application of best practice evaluation methodology to account for selection bias and, hence, to estimate the additionality (crowding out) of programme participation.

2 RECOMMENDATIONS ON THE DESIGN AND IMPLEMENTATION OF INNOVATION SUPPORT PROGRAMMES

2.1 MORE INCLUSIVESELECTION PROCEDURES TO WIDEN PARTICPATION

As the results from our econometric analysis show (see Executive Summary, Recommendation 8, above; and Del. 1.7) the actual selection process for the grant of support programmes does not lead to the best results. This analysis shows that a random selection would have better effects on the “return on innovation investment”. Thus policy makers should provide general conditions that enable more inclusive – or, at least, more random - selection processes. A main condition of this reform would be to increase the number of applications to innovation support programmes. Besides better marketing activities to promote these programmes, simplification of application procedures could be appropriate.

In connection to the desired expansion of target groups for innovation support measures, increased numbers of funded enterprises, especially those corporate forms dependent on support, need to be recognized. Developing more liberal awarding procedures is likely to raise the attractiveness of initiatives for a larger group of enterprises, and therefore allow a wider range of companies to participate in regional and national programmes.

Dedicated innovation support programmes, specifically designed for disadvantaged corporate organizations, including the applicability of certain budgets (e.g. for personnel and internationalization) could also be an approach to increase participation of the micro and small enterprises.

In close connection to liberalization of the awarding procedures of innovation support programmes towards an increase of applicants, and participants from a wide range of micro, small and medium enterprises, stands the interest of certain sectors to participate in a funded innovation project.

Innovation is not confined to R&D-intensive sectors. GPrix analysis highlights that the traditional sectors as well have considerable capacity for innovation. From Figure 5(included in Del. 1.7) we see a very high dependence of SMEs in traditional sectors on technological innovation: a very high proportion of sales is directly connected with innovation activities. Figure 5 is derived from the GPrix survey sample; it shows the percentage of respondents in each range of sales (0%, 1-5%, 6-10% and so on) derived from new or improved products or/and processes.

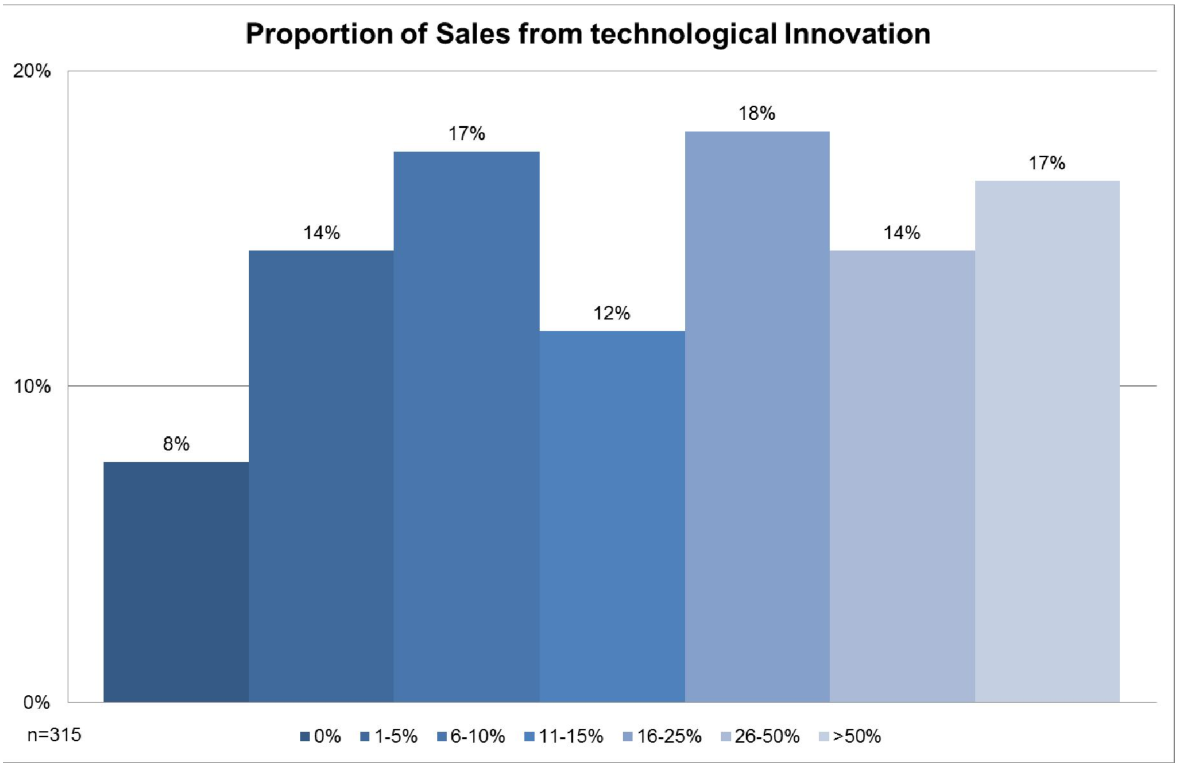

Figure 5: Proportion of sales from technological innovation (i.e. product or process innovation) [17]

To give a comparison to other sources, the following table shows different percentages of sales from technological innovation from countries represented in the GPrix sample. The Table 2 compares high technology industry with other industry and knowledge-intensive services. The traditional sector analysed in the GPrix sample is the most comparable to “other industry”.

Country	Percentage of Sales with new products (2008)			
	High Technology	Other industry	Knowledge-intensive services	Overall
DE	39%	13%	14%	22%
ES	29%	18%	17%	20%
FR	24%	13%	10%	16%
GB	10%	10%	5%	7%
IT	19%	10%	17%	14%
NL	17%	8%	13%	12%
PT	N/A	N/A	N/A	N/A

Table 2: Comparison of proportion of sales with new products[18]

In times of crises, innovation investments drop and their focus shifts towards economically critical business areas. During these times, enterprises need special support to maintain their desired long-run level of innovation.

Research-intensive businesses, referred to as high technology and knowledge-intensive services, receive a very large share of innovation support measure benefits compared to non-research

[17]Del. 1.7, see page 27.

[18]See: ZEW 2011b, p. 77 (see Deliverable 1.7 for the detailed reference).

intensive enterprises. Table 3 functions as a rough basis of comparison; “Other industry” is the nearest comparison to the GPrix traditional sectors. All values in the GPrix regional samples are much higher than the corresponding nation-wide mean values shown in Table 3. For example in Table 3 Germany had 20 per cent of companies with public financial innovation support in 2008 whereas the GPrix sample has around 50 per cent of participants from Germany using one or more innovation support measures. This is because the GPrix survey used a species of stratified sampling to ensure a sufficient number of responses from programme participants to enable analysis.

Country	Share of innovation active companies with public financial innovation support 2008				
	High Technology	**Other industry**	**Knowledge-intensive services**	**Overall**	GPrix
DE	**26%**	**18%**	**17%**	**20%**	51%
FR	**23%**	**18%**	**19%**	**20%**	41%
GB	**N/A**	**N/A**	**N/A**	**N/A**	33%
IT	**36%**	**35%**	**27%**	**35%**	33%
ES	**35%**	**26%**	**34%**	**30%**	59%
NL	**50%**	**33%**	**27%**	**34%**	37%
PT	**N/A**	**N/A**	**N/A**	**N/A**	48%

Table 3: Comparison of innovation active companies with public financial innovation support[19]

Both the traditional sector and research-intensive businesses are dependent on technological innovation. However, the latter use supportive initiatives more often than non-traditional and non-research intensive enterprises, as they represent their core business. This situation might be supported by common selection procedures of programme managers. They are likely to choose known, successful and relevant applicants before unknown, inexperienced enterprises and thus contribute to the uniformity of the innovation landscape.

To increase the diversity of this landscape it is important to inform all potential beneficiaries about existing possibilities on informative events or workshops as a first step.

As mentioned before, a change of awarding procedures is also crucial and can be approached by an increase of random selection procedures or the removal of participation obstacles. They could ensure a more inclusive awarding process.

Most of the GPrix survey sample uses innovation support measures to boost their activities in terms of timeliness and effectiveness. Questions 26 and 30on the GPrix questionnaire concerned the impact of having *not* undertaken their first and second support measures. In the event of having participated in at least one support programme, SMEs were asked to respond to the following question: “Would you have taken the same or similar steps without this public support?” Figure 6 derived from the GPrix survey database shows that around every second SME answered with “Yes – but more slowly and less effectively”; more than a third of SMEs answered “No – not at all” (i.e. they would not have undertaken the innovation activities without support); and only 10 per cent answered “Yes – and as quickly”.

[19] GPrix Consortium, De.1.7, p. 30.

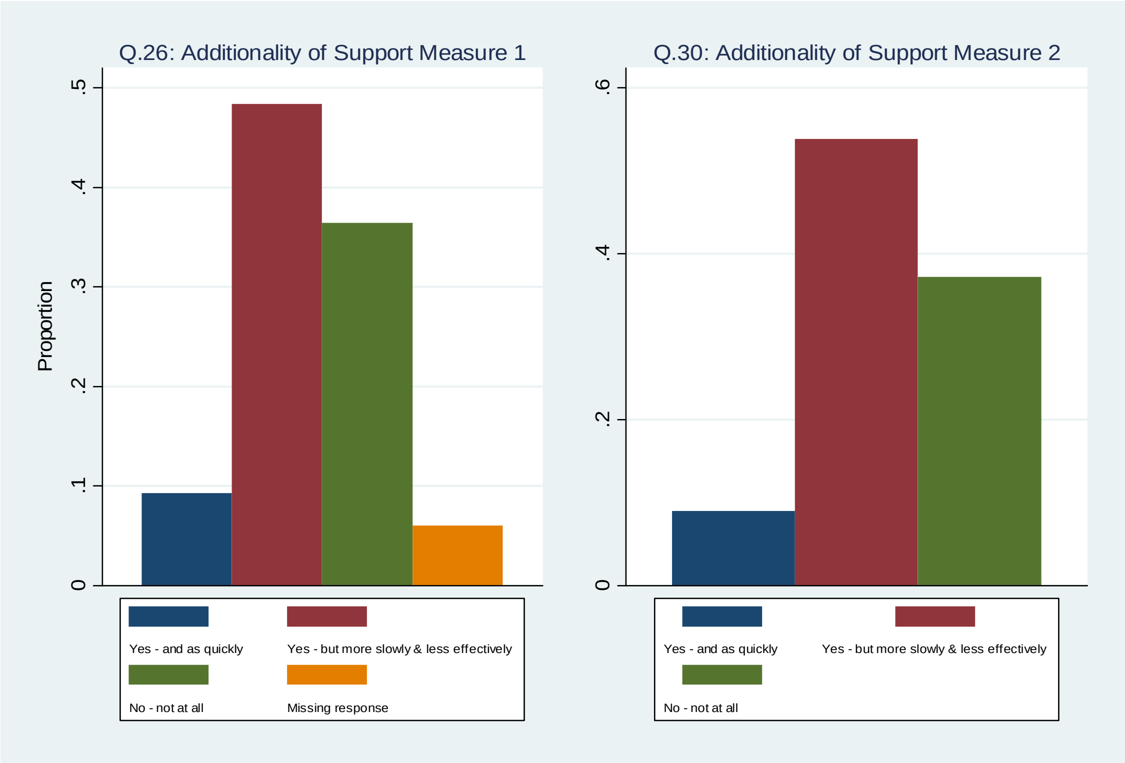

Figure 6: Additionality of support measures 1 and 2

Traditional sector SME responses on the impact of the support measures they have experienced are overwhelmingly positive, notably with respect to the timeliness of measures but also with respect to their effectiveness. Yet reality shows that programme budgets are sometimes not fully exploited, due to topic and target group restrictions.[20] To fully exploit programme budgets and therewith support those enterprises in special need of financial support, it is indispensable that all costs related to innovation measures within a company/project are considered eligible. Policy makers and program managers need to reconsider the alignment of innovation support programmes with the innovation models of SMEs in traditional sectors. Opening borders with respect to finances might increase interest among potential applicants and, furthermore, the participation of underrepresented groups.

[20]GPrix Consortium, Del1.7, p. 134ff.

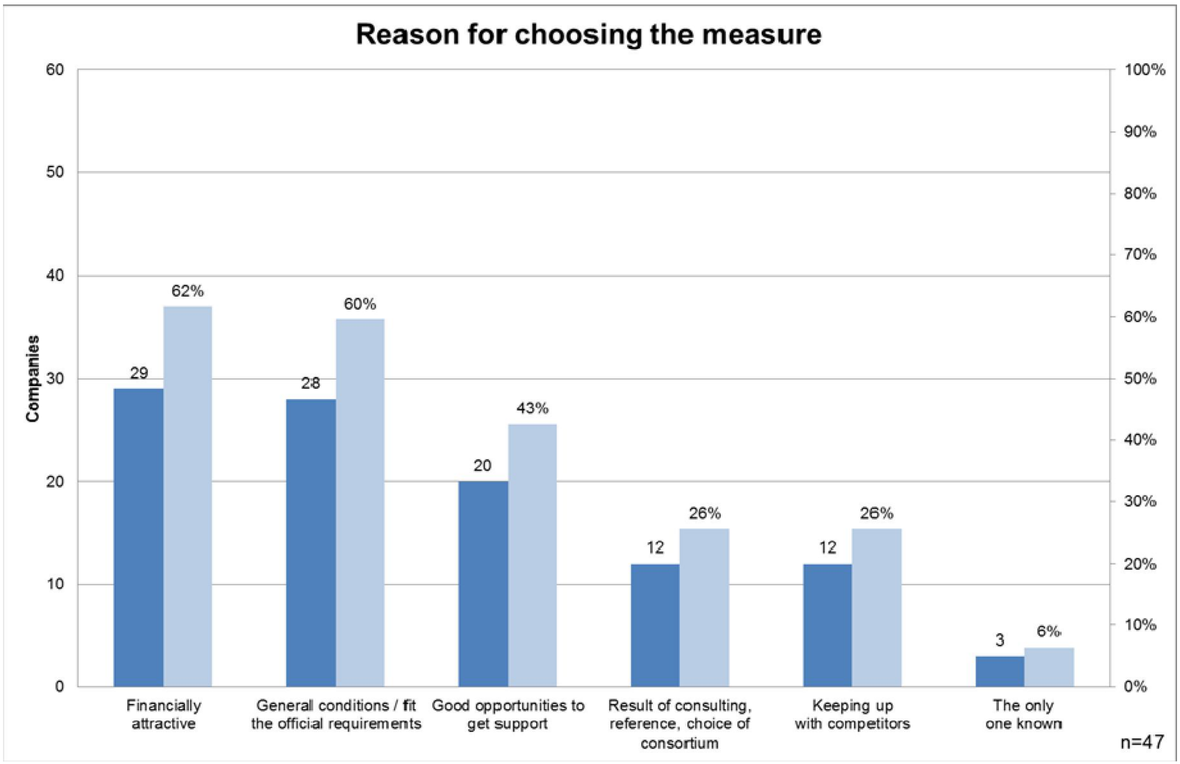

Figure 7: Companies' reasons for choosing innovation measures[21]

Additionality: a note on the apparent inconsistency between the survey descriptive Figure 6) and the econometric evidence.

The GPrix questionnaire was designed according to the principle of using questions established by previous studies where possible but creating new questions where necessary. Questions 26 and 30 are well established questions and responses are typically used to assess additionality. Yet the responses depicted in Figure 6 are at odds with the apparently more pessimistic conclusion of the econometric analysis; namely, that support programme additionality is, at best, negligible. This is an issue for GPrix as well as for other researchers using this question.

The explanation for this discrepancy may be that SME respondents are not good at assessing the counterfactual of what would have happened had their firm not participated in a support measure. However, even if this is the case, there may be value in the relative weight of responses, which suggests that additionality occurs less with respect to the innovation outcome as such and more with respect to its timeliness. While this explanation questions the validity of the question as a means of generating information about additionality, the qualification suggests that this question might indeed yield useful insight.

2.2 DEMAND LED PROGRAMMES

Development of specifically designed measures, such as demand-led programmes (e.g. Innovation Vouchers) or bottom-up initiatives could add to a more diverse innovation space of applicants and finally beneficiaries. Demand led programmes are more generic than specific and can be characterized as follows:

[21] GPrix Consortium, Del1.7, p. 36.

1. Covering the overall innovation life cycle from the first idea to market entry
2. Broad focus on different innovation types (product, process, organisation and marketing – i.e. both technological and non-technological innovation)
3. Wide eligibility of different costs
4. Flexibility in using the applied budget (internal budget shifts)

Thus a demand-led programme is a way to achieve customised projects for SMEs.

To cover the innovation life cycle completely, SMEs often need external support. The "Syntens Funnel" [22] from the Netherlands can be seen as a good practice approach: it is a business support network of 15 regional centres (270 consultants) in the Netherlands. They visit firms, do assessments, identify needs, promote participation in networks, help SMEs with innovation action planning, and refer them to appropriate experts and support programmes (including: vouchers; Innovation Officers; and the 'Design Pressure Cooker').Moreover, Syntens and the Chamber of Commerce track down companies that have not been supported before and are not yet familiar with the innovation networks in the region. It is a pro-active campaign: 700 SMEs have been visited; 55% were interested in innovation activities and referred to a follow-up trajectory. Figure 8 depicts the "Syntens Funnel" approach.

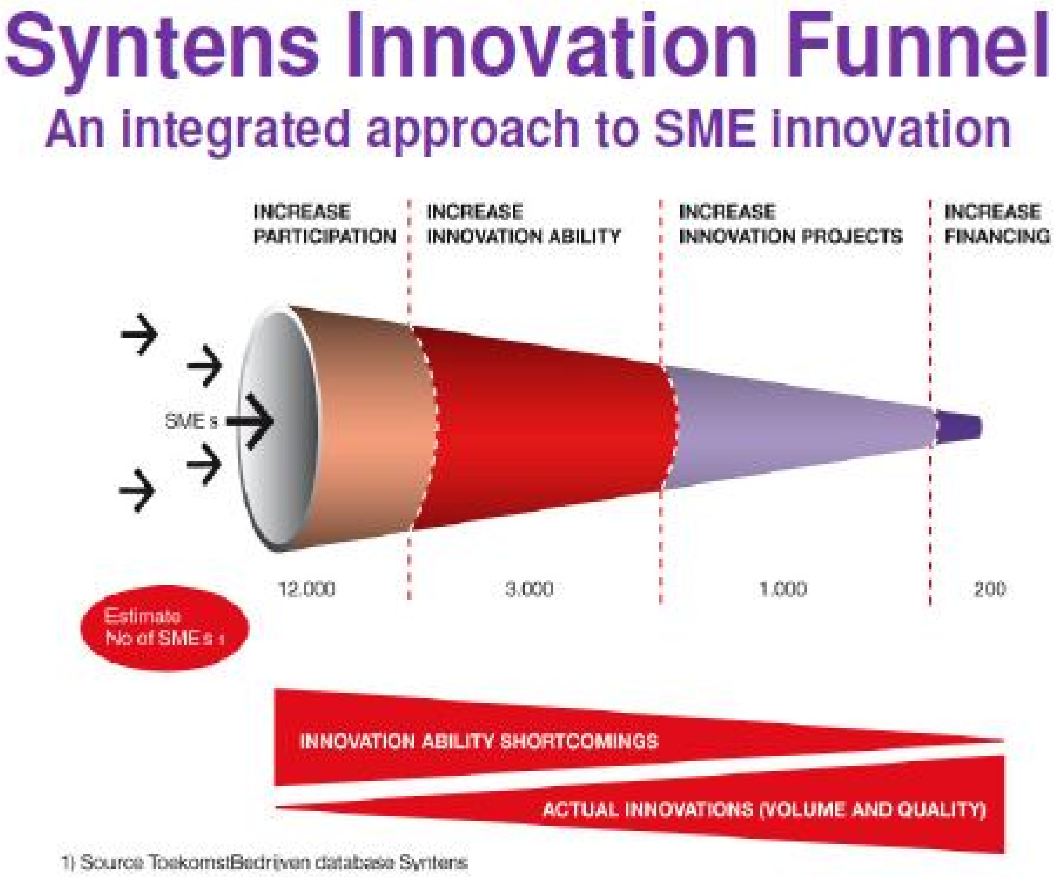

Figure 8: Syntens Funnel approach

[22] See "An integrated approach to increase SME innovation" in www.syntens.nl/eu/Pages/home.aspx

3 GENERAL RECOMMENDATIONS

3.1 INCREASING PRACTICABILITY AND FLEXIBILITY

As has been shown in previous sections, from the perspective of the innovation models and support needs of SMEs in traditional manufacturing industries the European innovation landscape suffers from one-sidedness and a lack of diversity. The reasons for this are:

- lack of marketing for innovation support measures to attract a wide range of potential beneficiaries;
- above-average representation of research intensive enterprises in innovation support programmes; and
- restricted programme access and "cherry picking" selection procedures.

According to these findings, current support policies and programmes do not fulfil the requirements of all interested parties, especially those of small and medium-sized enterprises in traditional manufacturing industries. For several reasons (e.g. restricted resources and focus on immediate operational matters) they are dependent on financial aid gained through innovation support programmes and need to rely on the applicability of these measures, regarding

- access to the programmes,
- support in application procedures,
- administration and
- coaching/mentoring.

Findings of previous analyses (e.g. from the MAPEER project) present a picture of innovation support programmes that lack practicability and flexibility. To discover the programme characteristics that encourage SME participation, the GPrix questionnaire included the following Question (31): "What are the specific needs for SMEs to enable them to participate in innovation support?" The responses are summarised in Figure 9.

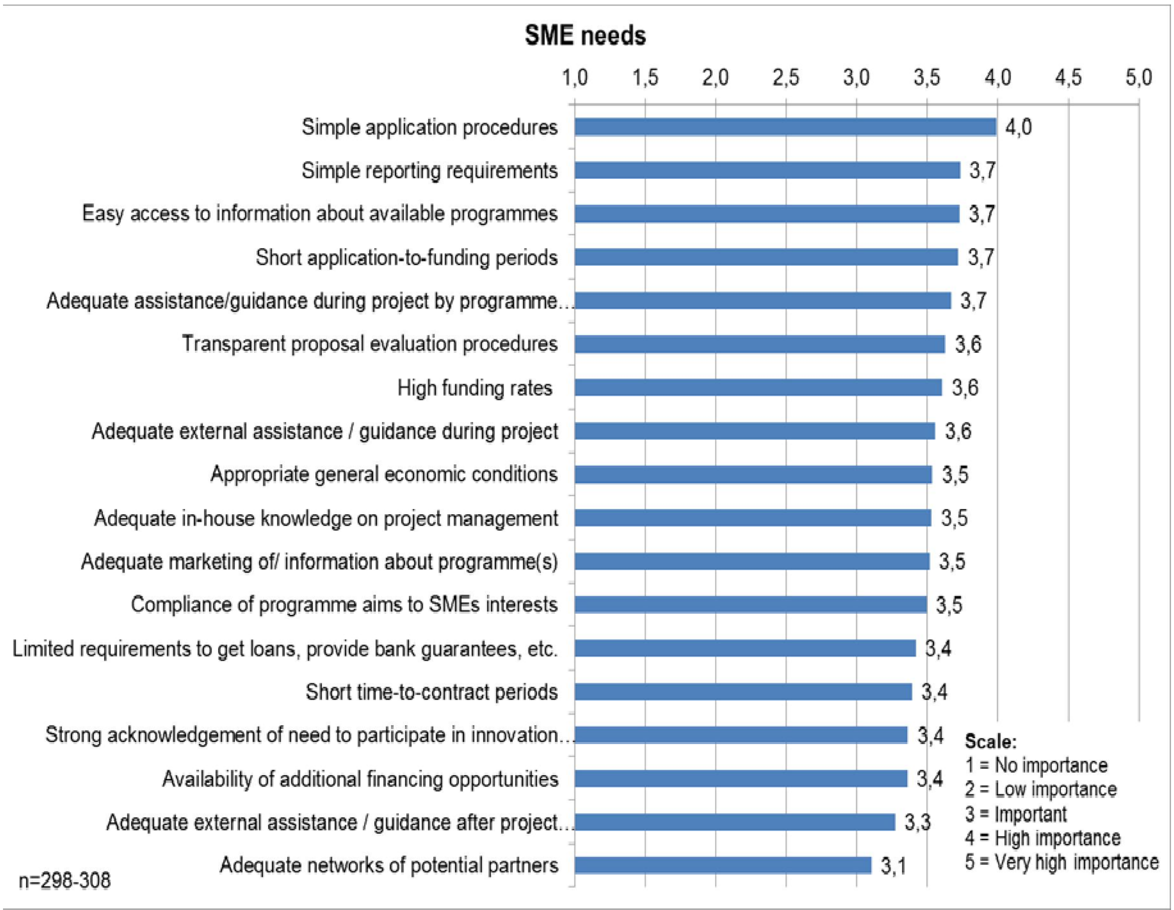

Figure 9: SMEs' needs to enable participation in innovation support programmes[23]

As Figure 9 shows, SMEs most often have difficulties with bureaucratic procedures and the complexity of programme documents. To increase practicability as well as flexibility a simplification of application, administration and reporting procedures and documents is necessary. This is especially important, as SMEs only have restricted resources to put to these issues, which are typically very time-consuming.

To sum up, the GPrix consortium recommends two directions of reform:

1. Simple and speedy procedures:
    a. Reduce bureaucracy!
    b. Do quickly!
    c. Pay quickly!
2. Provide guidance during the project:
    a. Mentoring
    b. Coaching

[23] GPrix Consortium, Del1.7, p. 41.

3.2 PROGRAMME EVALUATION

Another core result of the GPrix research is generally missing evaluation of innovation support programmes. According to the statements of programme managers, most of the considered support programmes measures have not been evaluated at all.[24]And such evaluation as has been undertaken falls well below best practice standards and is thus not informative about programme effectiveness. This is consistent with what the OECD had already stated in 2007 in relation to business support programmes more generally:

> Whilst there are examples of high quality evaluations, this is not the norm […] there remain too few examples of top quality evaluations […] about […] the impact which policy changes have upon SMEs and the economy more widely.[25]

The characteristics of “best practice” evaluation are the following:

- Use of a comparison group: participants compared with non-participants
- Measurement of additionality: accounting for selection bias
- Mixed methods approach: quantitative research (survey data: descriptive statistics together with modelling) combined with qualitative research (Interviews to inform case studies)

To realize all the above mentioned approaches to generally improve innovation support programmes, it is necessary to establish evaluation mechanisms to inform future initiatives. It is thinkable to implement certain state of the art procedures for all innovation programmes to generalize their evaluation, considering:

- structured data gathering before, during and after programme participation;
- sharing of lessons learned and best practice among participants, policy makers and programme managers; and, finally,
- inclusion of best practice evaluation costs into programme budgets.

3.3 PROGRAMME MARKETING

To further increase the level of information on relevant support measures, dedicated information and networking events should be realized in the first place. Potential beneficiaries, especially target groups, should be directly addressed and supplied with all relevant information. This might be in the form of personal assistance, support through help desks and hotlines, through various media as well as by benefitting from networks.

Special programmes for “first time innovators” are recommended, but have to reach their target group. Micro enterprises without R&D&I often do not know that there is special support for them. Programme managers typically do not undertake “activating” marketing, but just provide information (website, brochures). Yet, to reach special, uninformed target groups, the pure information providing approach is not enough; because if you do not know that there exist special offers for your company you will not seek them out. Here the recommendation is to use promoters (SME associations in traditional sectors) or direct marketing.

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[24] GPrix Consortium, Del1.5, p. 136.

[25]*OECD Framework for the Evaluation of SME and Entrepreneurship Policies and Programmes* (3rd Edition, 2007) pp.11-12. Paris. Available on-line.

4 REGIONAL/NATIONAL SPECIFICS

4.1 PORTUGAL

4.2 FRANCE

4.3 ITALY - EMILIA-ROMAGNA

The High Technology Network is one of the main initiatives of Emilia-Romagna Regional Government to bring together the research community and enterprises to strengthen the competitiveness of the industrial fabric. It is composed by 10 premises, one in each province and two in Bologna, hosting activities, services and structure networking Universities, Research centres and enterprises.

The Technopoles:

- are physical spaces in which the industrial research labs of the Emilia-Romagna High Technology Network are located. They are equipped with modern research facilities and provide services to the business sector;
- incorporate service organizations which carry out dissemination, demonstration, information and first assistance activities, provide office space for innovative spin-offs and for private research laboratories;
- promote the interaction between researchers and business sector representatives, favour the access to cutting edge scientific equipment bridging the gap between research demand and offer;
- act as access points to the entire High Technology Network dislocated throughout the regional territory sustaining its national and international projection.

SMEs, which represent the backbone of the regional productive system, are the major stakeholders and beneficiaries of the research activities carried out within the High Technology Network. These principles are reflected in the analyzed R&D&I programmes of the region aimed to support:

- industrial research and/or precompetitive development projects
- the start-up of new innovative enterprises
- collaborative research project of SMEs
- introduction of ICT in the SMEs
- realization of enterprise networks for the technological and organizational innovation in the SMEs

From the interviews with programme managers it was highlighted that SMEs express their interests for these research programs because they allow collaboration both with University and Large Enterprises on innovative projects, favouring SMEs' visibility and credibility in the market.

On the other side the specific needs expressed by SMEs in participation R&D&I support programmes are concerned with administrative and financial aspects.
The complexity of administrative procedures is an issue that is often found in our analysis. It also means a greater demand for assistance from the program managers during the implementation phase of the projects, which according to the interviewed SMEs is not adequate.

The main barriers related to the financial aspects are: lack of in-house funds, difficulties to access to external financing sources, innovation costs too high. In particular owing to the financial crisis, SMEs find many difficulties to find additional resources to coofinance research projects. This has influenced SMEs behaviour which concentrated their efforts in reducing costs.

Regional specific on innovation support measures to be considered for better structuring regional R&D&I support programmes are:

- R&D&I linkages with universities and research institutes
- Formation of new partnerships and networks
- R&D&I linkages with other business organizations
- Establishment of regional critical mass of R&D&I
- Enhanced knowledge and competences.

4.4 UNITED KINGDOM

Deliverable 3.3 already draws extensively on research and analysis from the British West Midlands. All of the 10 recommendations apply. However, the recommendation for institutional stability applies with particular force to the UK, while current reforms to the UK R&D tax credit appear already to be moving in the direction recommended by GPrix.

4.5 SPAIN

4.6 GERMANY – SAXONY-ANHALT

As displayed in Del. 1.2 (>>SWOT analysis and SME profiling of targeted regions<<) the strategic guiding principles of the government of Saxony-Anhalt towards the regional innovation improvement are:

- Expanding existing innovation focus and acting on new topics (e.g. Patent Promotion, Saxony-Anhalt IDEA, Research Voucher)
- Perfecting innovation-oriented infrastructure and supporting established work structures (cooperation, networks, cluster approaches) (e.g. Innovation Managers, Transfer of Knowledge and Technology)
- Strengthening and stabilizing contributions of universities and universities of applied sciences and non-university research facilities as innovation and economic factors
- Improve processes in the knowledge and technology transfer (e.g. R&D&I Promotion, Saxony-Anhalt IDEA, Transfer of Knowledge and Technology)
- Training skilled workers specifically for requirements of the industry and further qualifying them (e.g. R&D&I Promotion, Innovation Managers)
- Support and strengthen innovative knowledge- based business formations during the launch phase (e.g. Innovation Managers, Research Voucher)
- Further developing inter-agency integrated use of Land funding
- Continuing interlocking of land funding with federal government competitions and specifically using EU funding

These principles are also mirrored in the six analysed R&D&I programmes of the region (Del. 1.5 >>7 regional reports with an analysis of regional R&D&I policies in the 7 target regions<<), namely R&D&I Promotion, Innovation Managers, Patent Promotion, Saxony-Anhalt IDEA, Transfer of Knowledge and Technology, Research Voucher. Together they support and address certain aspects of governmental innovation policies.

With establishing the IB Saxony-Anhalt as single programmes manager of these initiatives, the government took a major step in introducing a central institution coordinating and fostering innovation activities among micro-enterprises and SMEs of the region. Its advisory centre provides all relevant information on existing innovation support programmes and gives extensive counselling in identifying appropriate funds for the demands of enterprises. Thus interested enterprises have the possibility to use this assistance in coping with their challenges.

Still, the analyses show that regional enterprises and policy makers face different obstacles in realizing innovation activities. Micro enterprises and SMEs feel that certain aspects aren't addressed appropriately by the policy makers/programmes manager and/or specific innovation programmes. At the same time, policy makers/programme managers report potentials for the development of innovation programmes. They can be summarized as follows:

- Simplification of access to innovation programmes
- Specific support for inexperienced enterprises
- Training of qualified employees
- Dedicated initiatives for certain sectors
- Evaluation of innovation programmes

In consideration of the SWOT analysis on national/regional settings within Del. 1.2, there are two main issues resulting from the evaluation for Saxony-Anhalt (1) training of qualified employees and (2) evaluation of innovation programmes. Both these aspects are especially important for the region for different reasons:

As Saxony-Anhalt is facing a population decrease and emigration of educated staff for economic reasons, it is necessary to either increase the attractiveness of the region for skilled persons. This could be done on several ways, as the resources are diverse. Trained persons who leave the region for better salary and living conditions likely stay when facing a more profitable employment market, providing e.g. possibilities for advanced training/qualification. Thus innovation programmes covering the employment of (professional) staff will probably support such a development. Furthermore collaborations and networks among institutions for higher education and enterprises hold the chance to fill the lack of qualified people.

To design innovation programmes, also dedicated to this specific issue, it is necessary to evaluate the success of completed innovation support measures and their related programmes. These evaluations could be valuable to subsequent initiatives, as they help to identify weaknesses and thus show opportunities for future actions.

4.7 THE NETHERLANDS

Appendix: Working Paper reporting the econometric evaluation in full

The impact of innovation support programmes on SME innovation in traditional manufacturing industries: an evaluation for seven EU regions

,
Dragana Radicic (Staffordshire University Business School)
Geoff Pugh (Staffordshire University Business School)

ABSTRACT

Innovation support programmes in the EU typically adopt a "cream-skimming" selection strategy: namely, programme managers systematically select firms on the basis of the observable characteristics most conducive to innovation. This study investigates the impact of innovation support programmes on SME innovation in traditional manufacturing industries in seven EU regions. 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. We find that innovation support programmes do not increase innovation by participating firms but could be effective in promoting innovation if applied to the wider population of SMEs, most of which, at present, do not participate. The policy corollary is that the effectiveness of innovation support programmes can be improved by more inclusive selection criteria for programme participation.

1. INTRODUCTION

This paper reports econometric investigation of a recent questionnaire survey designed to investigate the effectiveness of public innovation support programmes for small and medium enterprises (SMEs) in traditional manufacturing industries. This survey was conducted as part of the multi-methods GPrix project commissioned by the European Union's DG-Research.[1]

Economic theory posits that the rationale for innovation support measures is based on overcoming a certain type of market failure, i.e. knowledge is considered as a public good which leads to a positive externality (spillover effect). In turn, firms face difficulties in internalizing returns on innovation, and the end result is that firms will produce knowledge, embodied in innovation, under the socially optimal level (Arrow, 1962). Moreover, there are other types of market failure which could induce firms to innovate less than is socially desirable, such as imperfect capital markets, high barriers to entry and exit, market power etc. (Cerulli, 2010). Yet, the effectiveness of public support might be reduced if firms substitute private investment by public funding (Hussinger, 2008). In theory, therefore, public support might enhance private investment (additionality) but besides this there is also the possibility of crowding out. In recent years, empirical analysis of the impact of public support on firms' innovative activities has been mainly concerned with providing evidence on additionality/crowding out. Furthermore, 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' innovativeness (operational innovations and innovative sales).

The central aspect of innovation policy evaluation is the issue of endogeneity. Public funding cannot be treated as exogenous, because both innovation investment and public subsidies are codetermined, i.e. government agencies choose firms not through random selection but by "cream skimming" (firms that are more innovative are more likely to receive a subsidy). The issue of endogeneity arises from both self-selection of firms (firms that are more innovative are more likely to apply for a subsidy) and the selection of firms by government agencies (firms that are more innovative are more likely to receive a subsidy).

Finally, various empirical strategies are employed in innovation policy evaluation. 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 the selection models, which we employ in our analysis, control for both selection on observables and selection on unobservables (Cerulli and Poti, 2008).

We find that innovation support programmes do not increase innovation by participating firms but could be effective in promoting innovation if applied to the wider population of SMEs, most of which, at present, do not participate. The policy corollary is that the effectiveness of innovation support programmes can be improved by more inclusive selection criteria for programme participation.

The remaining of this paper is organised as follows: Section 2 reviews the empirical literature; Section 3 describes the empirical model; Section 4 presents the data; Section 5 discusses the estimation technique; Section 6 presents and interprets the empirical results; and Section 7 concludes and sets out the policy implications.

[1] Project full name: 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. http://www.gprix.eu/

2. LITERATURE REVIEW AND HYPOTHESES

The literature on innovation policy evaluation lacks clarity in defining the additionality effect. First, the authors agree that additionality represents the increase in R&D intensity (or innovation intensity, depending on the narrow or broader perspective on innovation) induced by a subsidy. '...This study is restricted to an estimation of additionality, this being defined as the increase in R&D intensity in firms, generated by R&D subsidies' (Heijs and Herrera, 2004, p.3). However, the confusion arises in determining the exact magnitude of the increase in innovation intensity. Some authors argue that any increase in innovation intensity can be regarded as additionality (Heijs and Herrera, 2004). Others note that additionality refers to the increase in innovation intensity larger than the amount of subsidy (Cerulli and Poti, 2008).

Conversely, there is a consensus in defining full and partial crowding out effects. Full crowding out refers to ' a complete substitution of private by public funds, and this means that firms' total R&D expenses would be the same with or without subsidies' (Gonzales and Pazo, 2008, p. 372). Cerulli and Poti (2008, p.11) provide a very similar definition: '*total crowding-out*: when the private R&D, compared to what firm would have done in absence of the grant, remains the same' (see also Busom, 2000; Gonzales and Pazo, 2008; Streicher et al., 2004). Therefore, a full crowding out effect implies that a firm reduces its private spending by the amount of the subsidy, so the total spending including a subsidy is the same had the firm not receive a subsidy. Finally, partial crowding out refers to a partial substitution of private spending. Partial crowding out occurs if firms raise their total R&D, but this amount is smaller than the subsidy itself (Gonzales and Pazo, 2008, p. 372) (see also Cerulli and Poti, 2008; Streicher et al., 2004).

In addition to distinguishing between additionality versus crowding out effect, innovation policy literature recognizes three types of additionality (Streicher et al., 2004):

- input additionality refers to the effect of support measures on the private R&D expenditures;
- output additionality refers to the impact of subsidies on firm performance (innovative sales, productivity, growth in turnover and/or employment, profitability); and
- behavioural additionality refers to changes in firms' innovative behaviour induced by public support measures.

Figure 1 gives a graphical presentation of output additionality and crowding out according to the definitions followed in this paper:

- *Additionality*: the firm does not reduce its own innovation; instead, the firm's innovation is greater than it otherwise would have been by an amount in addition to the firm's own innovation brought about by the support measure.
- Full crowding out: the firm reduces its innovation by an amount equal to the innovation brought about by the support measure; hence, the firm's total innovation with the support measure is not greater than it would otherwise have been (the support measure substitutes fully for the firm's own efforts).
- Partial crowding out: the firm reduces its innovation but by an amount less than the innovation brought about by the support measure; hence, the firm's total innovation is greater than it would otherwise have been but by an amount less than the full effect of the support measure (the support measure substitutes partly for the firm's own efforts)

Figure 1. Innovation output: output additionality and crowding out

No support programme			With a support programme				
			Additionality		Full crowding out		Partial crowding out
		Total innovation	Innovation resulting from the support measure				
						Total innovation	Innovation resulting from the support measure
Total innovation	Firm's own innovation		Firm's own innovation (≡ Innovation without a support measure)	Total innovation	Innovation resulting from the support measure		Firm's own innovation (< Innovation without a support measure)
					Firm's own innovation (< Innovation without a support measure)		

Following Garcia-Quevedo (2004), the theoretical considerations of the additionality versus crowding-out effect of private innovation subsidies imply that both effects are plausible.[2] Public support might provide incentives for firms to increase their investment in innovation, but might also lead to decline in innovative activities, as public funds substitute for private R&D investments. David et al. (2000) provide an extensive review of empirical evidence regarding the effect of public support on innovation and conclude that, although more empirical studies indicate complementarity rather than substitutability between public and private R&D funding, the overall conclusion is still ambiguous. Lindstrom and Heshmati (2005) in their review of more recent empirical evidence, 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.

Another conclusion from Garcia-Quevedo (2004) is that the problem of establishing control groups severely impedes the evaluation of public support, which implies that policy-makers should incorporate the requirements of best practice evaluation into the design and budget of innovation policies. Furthermore, comparison between studies is hampered by the lack of a common methodology for public policy evaluation. Best practice evaluation methodology is characterised by the use of a control group – or, at least – a comparison group - and a serious approach to selection bias: Garcia-Quevedo (2004) insist that government support should always be treated as endogenous, due to the simultaneity and selection bias in the process of applying for support and in the selection process. As Lindstrom and Heshmati (2005, p.5) observe: 'It is well documented in the literature that firms funded by the government are likely to be among those with the best ideas.'

[2] Most empirical research to date deals with R&D subsidies, which is not surprising, as public policy was focused and is largely still focused on R&D activities, rather than on innovation in a broader sense as defined in the OECD *Oslo Manual* (2005).

Most empirical studies in the last decade have analysed the Community Innovation Survey (CIS) datasets across countries, using different waves of the survey. As Czarnitzki and Lopes Bento (2010) note, the cross-sectional nature of CIS data prevents researchers from applying certain estimation strategies, such as the difference-in-differences estimator. Furthermore, Instrumental Variable (IV) estimation and switching models may not be applicable, because the CIS data often lack valid instruments for the treatment variable. Hence, 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. Therefore, in our study we apply the selection (switching) model, which controls for both observed and unobserved heterogeneity. On the other hand, the selection models are based on the strong assumption of the normality in the functional form, whereas the matching method does not require any assumption regarding the functional form (Hussinger, 2008).

Czarnitzki and Lopes Bento (2010) analyse the impact of public support on innovation intensity [3] and on the internal R&D investment in five countries - Belgium, Germany, Luxembourg, Spain and South Africa. The sample covers only innovative firms for both manufacturing and service sectors. They apply the matching estimator and find that the full crowding out effect can be rejected. An interesting feature of their study is the analysis of the average treatment on the untreated effect (ATU). The results indicate that non-participating firms would have increased their innovation activities had they participated. The results hold for each country except South Africa. Finally, Czarnitzki and Lopes Bento (2010) argue that if the ATU effect is greater than the ATT, this would indicate the misallocation of the public funding. However, their analysis does not indicate that the public subsidies are systematically misallocated.

Lindstrom and Heshmati (2005) investigate the impact of public R&D subsidies on the R&D intensity in Sweden using the CIS3 data. They apply a non-parametric matching approach based on the propensity score. Their results are interesting insofar as additionality of public support is found only for small firms (10-50 employees, as defined in their study), whereas the full crowding-out effect can be rejected regardless of the firm size.

Heijs and Herrera (2004) analyse the effect of R&D subsidies on the R&D intensity of Spanish manufacturing firms in the period 1998-2000. They also employ Propensity Score Matching, and the reasons for selecting this approach are as aforementioned. The first interesting finding stems from analysing subsamples of firms based on firm size. Small firms are less likely to participate than medium-sized and large firms. Here, the authors note that the government agencies adopt the strategy of "picking-the-winner" from large and medium-sized firms. In addition, the authors suggest two other potential explanations. First, small firms have limited human resources, which impedes their application process; i.e. gathering information on different sources of public support and preparation of the application forms is time-consuming. Second, often public support is directed towards R&D projects, which implies that small firms without formal R&D departments are highly unlikely to be eligible. The second relevant finding is that the coefficients on all three variables indicating innovative behaviour (exporting, formal R&D activities and cooperation with other agents) have, by far, the highest marginal effects. The authors emphasize that this result is not due to the "picking-the-winner" strategy adopted by government agencies, but probably because less innovative firms self-select themselves into the selection process. The most interesting finding is related to the magnitude of the average treatment on the treated effect (ATT). On average, public support increases the R&D intensity by 1.59 percentage points. The authors notice that this is a very small effect but, on the other side, the results suggest that the crowding out effect can be rejected. However, the authors

[3] Innovation intensity is measured as the ratio of total innovation expenditures to sales.

conclude: 'Regardless of size, aid distribution process is clearly focused on results (picking the winners) ... A modern technology policy should not only stimulate R&D activities of already innovative firms, but also raise the number of innovative firms' (Heijs and Herrera, 2004, p.17).

Somewhat different results are reported by Busom (2000). She investigated the impact of public subsidies on the R&D intensity in Spanish firms in 1988. For the purpose of sensitivity analysis, the model of two equations (the selection and output equation) is estimated using three approaches: ordinary least squares (OLS) estimation; a sample selection model (Heckman two-step procedure); and maximum likelihood estimation. Contrary to Heijs and Herrera (2004), the results in this study indicate that small firms are more likely to receive public support than large firms. Furthermore, overall the results suggest additionality, i.e. public funding induces more private R&D investment. However, for 30 per cent of participating firms, a full crowding out effect cannot be rejected.

Almus and Czarnitzki (2001) estimated the effects of R&D subsidies on R&D intensity in Eastern Germany using the German pooled CIS datasets for the years 1995, 1997 and 1999. As in most other studies, the authors utilize a non-parametric matching approach. The results indicate the rejection of a full crowding out effect. Furthermore, the ATT effect is 3.94 per cent, indicating that support measures induce an increase of 3.94 per cent in the R&D intensity of participating firms.

Cerulli and Poti (2008) evaluate the effects of public support on R&D intensity using the Italian CIS3 dataset. Their study employs two empirical strategies: a non-parametric matching estimation procedure and a selection model (Heckman two-stage procedure). The results, which are very robust to different estimation procedures, indicate that a full crowding out effect can be ruled out. However, when analysing disaggregated subsamples of participating firms, the results indicate that a full crowding out effect occurs in very small firms (10-19 employees), low knowledge-intensive service sectors and in the automotive industry.

The studies reviewed so far investigated the effect of public policy on innovation input (R&D intensity), which is referred to as input additionality. Recently, Catozzella and Vivarelli (2011) estimate the impact of public support on innovative productivity by analysing the Italian CIS3 dataset. Innovative productivity is defined as the ratio between innovative sales and innovative expenditures. Therefore, this study takes into account both innovation input (expenditures) and innovation output (innovative sales). The model is estimated using a bivariate endogenous switching model. The ATT effect is estimated to be -4.95 percentage points. The authors interpret this as evidence that participating firm increase both innovation input and output as a result of public support, but that the increase in innovation expenditure (input) is larger than the increase in the innovation output (innovative sales), which results in the overall ATT effect having a negative sign.

Finally, Garcia and Mohnen (2010) explore the impact of public support on R&D intensity as well as innovation output in Austrian firms using the CIS3 dataset. Their study departs from other evaluations studies insofar as they use a structural model, similar to the Crepon-Duguet-Mairesse (CDM) model. This model enables the estimation of the effect of public support on both innovation input and output (innovative sales from new products). Another interesting feature of the study is that two sources of public support (central government support and EU support) are included in the analysis. Furthermore, the analysis distinguishes between degrees of novelty in product innovation, thus dividing it into two categories: new to the market; and new to the firm. The results vary depending on the source of funding; EU support has no effect on either innovation input or innovation output (for both products “new to the firm” and “new to the market”). However, central government support induces an increase in R&D intensity by

2.3 percentage points. Furthermore, central government support has a positive effect on both categories of product innovation, by increasing innovative sales of "new to firm" product innovations by 2.5 percentage points and by increasing innovative sales of "new to market" product innovations by 3.4 percentage points.

From our empirical literature review, it can be observed that recent studies in most cases find evidence of additionality of public support, although such additionality effects are small. Moreover, as already noted, these studies mainly focus on input additionality. Our empirical models, on the other side, focus on output additionality, i.e. the impact of support measures on innovation output (in our case, operational innovations and innovative sales). Therefore, it is hard to compare our results with the empirical evidence from other studies. The only exceptions are two studies: the findings from Catozzella and Vivarelli (2011) are in line with our own empirical findings of a negative ATT effect on product innovation; and the finding of Garcia and Mohnen (2010) of a positive effect of public support on innovative sales is broadly consistent with the results reported below. However, these two studies focus on product innovation, and our study encompasses all four innovation modes (product, process, organisational and marketing innovations) as well as innovative sales.

3. THE MODEL

1.1 SPECIFICATION

This section sets out a parsimonious model for econometric estimation of the innovation effects of programme participation on SMEs. The model was first set out publicly in Deliverable 1.3 of the GPrix project (GPrix, 2010, pp.11-21). This prepublication is notable for two reasons, one noting a cost, the other a benefit.

1. The model had to be used to derive a set of survey questions (see Appendix 1). Accordingly, model specification was constrained by the practicalities of survey research. The model had to be sufficiently well specified to estimate the effects of programme participation yet also sufficiently parsimonious to inform a questionnaire not exceeding the tolerable maximum length. The need for parsimony was reinforced by a decision to coordinate the GPrix survey with the survey from the complementary MAPEER project.[4] Because, to this end, a common core of questions was to be included in two otherwise very different surveys, their number necessarily had to be limited.
2. 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 selection bias in econometric literatures (Stanley, 2005).

Next, we briefly review the foundations of our modelling strategy: namely, best practice in programme evaluation; and the principles for specifying a "parsimonious" (i.e., minimal) model of innovation.

1.1.1 BEST PRACTICE IN PROGRAMME EVALUATION

The *OECD Framework for the Evaluation of SME and Entrepreneurship Policies and Programmes* (2007 pp.11-12) has this to say about the state of evaluation studies on SME support programmes:

> … whilst there are examples of high quality evaluations, this is not the norm … there remain too few examples of top quality evaluations … about … the impact which policy changes have upon SMEs and the economy more widely.

The methodological challenges to be confronted when evaluating innovation support programmes are explained in the OECD *Framework* (2007, pp.11 and 27; also, pp.50 and 52):

> Broadly, lower quality evaluations seem to produce more "favourable" outcomes for the project because they attribute observed change to the policy when this may not be justified … In contrast, the more sophisticated approaches strip out the other influences, and so only attribute to the programme its "real" effects … policy makers need to be aware that there is a risk that low grade evaluations … lead to misleading pictures of programme effectiveness.

[4] Both projects were commissioned by DG-Research in 2009: GPrix to evaluate innovation support for SMEs in traditional manufacturing industries; and MAPEER (http://mapeer-sme.eu/) to focus on R&D support for SMEs more generally.

To address these challenges, best practice quantitative evaluation methodology must include the following.[5]

1. A **comparison group of non-participants**, which provides an observable "counterfactual" to the programme participants. In turn, this enables quantitative estimation of *additionality*.

2. A **selection model**, which accounts for the non-random assignment of participants and non-participants. Even in the absence of innovation support programmes, firms that would participate if they had the opportunity and firms that would not participate if they had the opportunity may have different innovation outcomes: potential participants may be the firms most inclined to innovate; conversely, these might be the least able to innovate and thus the most inclined to seek external support. Unless such effects are allowed for in the model, they are falsely attributed to programme participation. A selection model is the means to account for such potential biases in estimating programme participation effects.

A selection model includes the following:

a. ***variables of interest***, i.e., indicators of
    i. innovation (the dependent variable - i.e., the variable to be explained) and
    ii. participation (the independent variable of interest - i.e., a potentially endogenous dummy variable representing the programme or type of programme whose effects on innovation we want to estimate);
b. ***control variables*** (i.e., all variables that may have an economically important effect on innovation other than programme participation); and
c. ***participation variables***, which influence whether or not a firm participates in an innovation support programme but which do *not* have a causal effect on whether or not a firm innovates (such variables are known as identifying variables, because they differentiate a model of participation from a model of innovation).

With these three types of variable, we can estimate the impact of programme participation on firms' innovation conditional on (i.e., controlling for) *both* other influences on innovation (the control variables) *and* the probability that the firm will participate in an innovation support programme (measured by the selection model). In the next sections, we address the main difficulties arising from this approach to programme evaluation.

1.1.2 SPECIFYING A PARSIMONIOUS MODEL OF INNOVATION

The first problem to address is that there are many potential control variables. Estimation of programme participation effects will not be impaired if we omit variables that have only a minor effect on innovation outcomes and that are not correlated with programme participation. However, this initial winnowing would still leave a list of potential variables too long either to be translated into a feasible questionnaire or to be included in an econometric model to be estimated on a relatively small dataset. Consequently, the next section outlines our approach to reducing the long list of potential variables to a minimum, practical list.

[5] The introduction to a recent collection of evaluation studies of business support programmes characterises good practice as follows (Lenihan et al., 2007, p.317): 'Increasingly, good practice in evaluation research at the level of the firm is pointing towards the use of econometric treatment models, e.g. two-step Heckman models, which account for 'selection' and 'assistance' effects …'

Literature review reveals a huge number of variables: for example, in a recent survey paper Becheikh et al. (2006) identify over 60 determinants of innovation. By taking an even more comprehensive view of the innovation literature - by including, for example, innovation studies from the literature on entrepreneurial psychology - many more determinants could be added. 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 (i.e., satisfying the principle of explaining the most from the least). In the presence of too many potential variables, we proceed as follows.

1. We are not interested in the control variables as such; their function is to enable accurate estimation of programme participation effects. Hence, we use dummy variables (i.e., binary indicator variables) wherever possible to aggregate the effects of the many possible individual effects.
    a. ***Country dummy variables*** (i.e., fixed effects) substitute 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 such as variations in the business cycle).
    b. ***Regional dummies*** substitute for all regional effects (i.e., all those variables associated with the "regional innovation systems" approach).
    c. ***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. In addition, we suggest an approach to constructing ***a firm level 'quasi' fixed effect*** (or initial condition) to capture *otherwise unobservable* firm and ownership effects. Here we adapt an approach suggested, albeit in a different context, 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 commercialise new products and processes" may 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.

Applying these principles, we next specify a parsimonious model for estimating the innovation effects of programme participation.

1.1.3 A PARSIMONIOUS MODEL OF INNOVATION

In accord with the preceding discussion, our model has two equations: the second equation models the participation decision (i.e., 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* (i.e., controlling for) both other influences on innovation and the probability of participating in an innovation support programme.

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

Subscript *i* indexes each firm in the sample 1…n, where n is the number of firms; *C* and *I* represent the constant/intercept in equations 1 and 2 respectively, to be estimated; the γ coefficient to be estimated measures the innovation effect of programme participation; the β and λ coefficients to be estimated 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 to be estimated that measure, respectively, the innovation and participation effects of 1×k vectors of *Industry*, *Region* and *Industry* dummies; the k×1 α and δ vectors contain coefficients to be estimated 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 to be estimated 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 identifying variables; and *u* and ε are the usual regression error terms, which capture the unobserved influences on the respective dependent variables. Precise definitions and descriptive statistics are presented in Table 1 below. The origin of each variable is given by the corresponding survey question(s), which are presented in Appendix 1.

Equation (1) models innovation outcomes and includes the following variables.

The dependent variable in equation (1) (*Innovation*) is an indicator variable for innovation output (= 1 if innovation takes place; = 0 if innovation does not take place. This approach enables us to investigate not only the four standard types of innovation separately (i.e., product, process, organisational and marketing) but also to disaggregate these to investigate potential heterogeneities (e.g., between product innovation in goods and in services).

Our variable of interest in equation (1) (*Participation*), is the programme participation indicator (= 1 if the firm participated in one or more support programmes; = 0 if it did not). We had hoped to make this a continuous variable measuring the total value of the support received, and to this end questions were included in the survey to elicit this data. However, subsequent interviews revealed that respondents generally did not know the value of the support received, which is manifested in suspect reliability of many survey responses (not only a high level of missing values compared to other questions but also many implausibly low and high values). Hence, in order to maximise the quantity and quality of the data used in estimation, we accepted the loss of information entailed in defining our participation variable in binary form. Such trade-offs are endemic in programme evaluation. For example, in the application undertaken by Aakvik et al. (2000, p.26) the authors acknowledge that the programme intervention (training) is heterogeneous with respect to substance, duration and effects.

In addition, we include the following control variables:

- firm's size (*Size*) measured by the enterprise's total number of employees in 2009;
- firm's market power/strength of competition (*MPower*) (= 1 if the firm responded "very strong" to the question "How would you judge the competition in your main market(s); otherwise 0);
- the percentage of the firm's turnover accounted for by exports (*Export*);
- industry fixed effects (dummy variables) (*Industry*) (the omitted category is "Other");
- country fixed effects (dummy variables) (*Country*) (the omitted category is the UK);[6] and
- quasi firm fixed effects (*QFFE*) - or initial conditions - which control for the 'permanent' capacity of the firm to innovate. This is modelled by five variables derived from questions to firms about their innovation behaviour at the beginning of the sample period:
  - resources devoted by the firm to innovation compared to the present (= 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 and process innovation (in each case, = 1 for "Above average" and "Leading"; = 0 for "Average" and "Lagging") together with organisational innovation and marketing innovation (in each case, = 1 for "Lagging"; = 0 for "Average", "Above average" and "Leading").

Equation (2) is the selection equation, which models the process that sorts firms into "participants" and "non-participants" in innovation support programmes. The dependent variable of equation (2) is *Participation*, as discussed above. The sorting process that determines the outcome of this variable (participation/nonparticipation) is likely to be influenced both by firms' observable characteristics and by unobservable (to the researcher) characteristics, both of which may influence selection biases on the part of programme managers and/or self-selection bias on the part of firms themselves. 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).[7] This identifying variable (*Obstacle*) must influence the programme participation decision but not the innovation decision. 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 Table 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 1 demonstrates that most of these display widely varying proportions between participants and nonparticipants. In practice, in each model estimated, at least two or three of these variables proved to act as they were designed to, namely as significant influences on selection but not on innovation.

[6] In the GPrix database, all firm responses come from one region in each country; hence, there is no separate *Region* fixed effect.

[7] 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'. We return to this theme at the end of Section 6 below.

4. THE DATA

In principle, the GPrix survey required a random sample from the population of SMEs in the six targeted traditional manufacturing sectors in the seven regions covered by the project. The practical difficulty to be confronted was the anticipation – arising from previous experience as well as the literature on survey responses - that it would be difficult to obtain large numbers of questionnaire responses from SMEs in traditional sectors. For this reason, each partner accepted a target of 100 responses which, in the event, was achieved only in the West Midlands.

Interview evidence gathered in the course of case study research in the GPrix project yielded several insights into the very low response rates from traditional sector SMEs. In brief the main reasons are as follows.

1. *Cultural barriers*. Owners and managers of traditional-sector SMEs typically have little or no contact with universities; and often owners and managers have no experience themselves of higher education. Accordingly, they are inclined to see little or no value in research.
2. *Owners and managers are too busy*. Typically, they have nobody to whom to delegate. Instead, SME owners and managers have to focus on immediate operational matters. Hence, non-essentials, which include completing questionnaires, are not a priority.
3. In addition, *SME owners and managers hate paperwork*, including questionnaires! Even trade associations, organizations that SMEs have chosen to join, find it difficult to obtain information from their own SME members.

Given the anticipated difficulty in obtaining responses, which was amply confirmed by our later experience, we proceeded as follows. For concreteness, we refer to the West Midland; however, all partners proceeded in a similar manner. According to secondary data from the UK Office of National Statistics, the GPrix sampling frame in the West Midlands comprised 6416 enterprises in the five traditional sectors of interest: leather; ceramics; textiles; metal; auto (the food processing sector was studied by some other partners but not in the West Midlands). A minor problem was that this population includes large as well as SMEs. However, any responses from large firms could be filtered out in later analysis to achieve a sample of SMEs (across the whole GPrix survey, nine from 333 responses were from firms with 250 or more employees). The major problem was that 100 responses per partner – the maximum feasible on practical grounds – would yield too few programme participants to answer the main questions to be investigated. For example, in the West Midlands, if we assume a 5 per cent response rate (a most optimistic assumption) then we could expect 321 responses. Yet the rates of participation by UK SMEs in the support programmes of interest range from a relatively high one per cent (e.g. Knowledge Transfer Programmes) through medium rates of less than 0.5 per cent (e.g. Designing Demand) to a relatively low (and more common) 0.1 per cent or lower (e.g. Innovation Vouchers; and Innovation Networks). Moreover, participation rates tend to be even lower among SMEs in traditional manufacturing. Accordingly, the expected number of responses for innovation support programmes would have ranged from a high of three (KTP participants) to a low of zero (Voucher participants). The implication is that a simple representative sample of all manufacturing SMEs in the five traditional sector of interest would include *insufficient programme participants for useful analysis*.

Accordingly, the GPrix project used a species of stratified sampling; i.e. a random sample biased in a deliberate way towards programme participants. The challenge was to generate a sample of SMEs in five target sectors of traditional manufacturing with a high proportion of programme participants. To this end, a two-fold approach was implemented:

1. to generate a sample of SMEs in five target sectors of traditional manufacturing to be representative in all respects *except* for programme participation; and
2. to ensure a sufficient number of programme participants to be able to address the issue of interest (i.e. programme effectiveness) the sample was deliberately biased to over-represent participants in support programmes.

In addition, we provided an "incentive" for all respondents (a prize draw for one of five £100 vouchers for either a top-class restaurant or a department store).

To align the sample frame as closely as possible with the target population we used, wherever possible, publicly available industry lists of SMEs to approach firms by e-mail or, where this was the only alternative, by post. Such lists were available from industry sources for the automotive sector, which substantially overlaps with the metallurgy/metal fabrication sector, the leather industry, and the textile industry. Other industry lists – e.g. for the ceramics industry - were secured with the help of trade associations, which enabled us to send e-mails to all their members in the West Midlands. In addition, sympathetic organizations publicized the survey via their web sites and/or through their newsletters: e.g. the two sub-regional Chambers of Commerce in the West Midlands. Finally, the survey was also publicized through business focused web lists and discussion forums.

To ensure a sufficient number of programme participants to be able to address the issue of interest (i.e. programme effectiveness), we enlisted the support of programme managers to send e-mails to all firms who had applied for support in the period 2005-09 (i.e. both participants and non-participants). Here we had uneven success: whereas the regional Innovation Voucher scheme sent out around 400 e-mails, giving complete coverage, other programmes gave incomplete coverage (for example, because they were administered nationally and did not keep regional lists).

This strategy was very resource intensive: around 2,500 questionnaires were sent out by post to SME owners and managing directors (plus a follow up mailing to non-respondents); several hundred more e-mails went to SMEs in the ceramics industry and in other sectors (plus a follow up e-mailing to non-respondents); more than 500 e-mails were sent via programme managers (plus a follow up e-mailing to non-respondents); and an unknown number of firms were reached by other, less precisely targeted means (at least many hundred; possibly several thousand). Altogether, a conservative estimate is that we approached at least 4000 firms (from a population of around 6,500). The 98 completed questionnaires returned give an overall response rate in the West Midlands of around 2½ percent. The other GPrix partners implemented a similar approach, which was arrived at by sharing experiences during the first year of the project. In total, completed responses were received from 333 firms in the target regions in 7 countries.

Detailed descriptive statistics on the survey sample are presented in Tables 1, 2 and 3 below. 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 except for innovation behaviour.

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%; 34%) to the UK (34%; 66%) (see Table 2 below). 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 firms – and economic position (e.g. market power/strength of competition) (see Table 1 below). Conversely, as expected, there are systematic differences between participants and non-participants in all categories of innovation.

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. Yet, differences with respect to innovation behaviour suggest that the analysis must control for selection bias. Accordingly, our modelling strategy is designed to identify additionality – i.e. the effects of programme participation on innovation outcomes over and above differences accounted for by observed and unobserved differences between participants and non-participants.

The data are restricted to SMEs in traditional manufacturing industries, which defines our population of interest. In turn, programme impact on firms randomly drawn from this population is relevant from the perspective of public policy designed to promote innovation by SMEs in traditional manufacturing industries (Wooldridge, 2002, pp.604-05).

The firms in the sample are independent legal entities and, even in the one case where more than one firm in the sample belongs to the same group, operate as separate entities. In addition, the sample firms operate in different industries and in different countries. Hence, we can assume that we satisfy the assumption of our estimator (see below) that we estimate our model on an independent, identically distributed (iid) sample from the population, which rules out cases where the treatment of one firm affects other firms' outcomes "possibly through general equilibrium effects" (Wooldridge, 2002, p.604; Aakvik, 2002, p.6). This is also known as the stable unit value assumption, which is implied by random sampling.

Table 1 sets out descriptive statistics for all the variables used in estimation.[8]

[8] 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.

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

Variable	Variable in the dataset	Participants (mean)	Nonparticipants (mean)
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)
Organisational innovation - new business practices for organising procedures	Q9_1_2	0.58 (0.49)	0.48 (0.50)
Organisational innovation - new methods of organising work responsibilities and decision making	Q9_2_2	0.47 (0.50)	0.40 (0.49)
Organisational innovation - new methods of organising external relations with other firms or public institutions	Q9_3_2	0.52 (0.50)	0.29 (0.46)
Organisational 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)
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 [9]	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)

[9] 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.

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 importance)	Q31_13t_5	0.20 (0.40)	0.12 (0.32)
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. 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).[10] 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 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. A similar pattern emerges for the disaggregated categories of product innovation: participants are more likely to introduce product innovation in goods, 83 per cent relative to 61 per cent of nonparticipants. Furthermore, 58 per cent of participants engage in product innovation in services, compared to 42 per cent of nonparticipants.

Almost all participants, i.e. 91 per cent, engaged in process innovation, whereas nonparticipants engaged to a lesser extent, 76 per cent. Again, a similar pattern is apparent for the disaggregated categories of process innovation. However, the difference between the probability of innovation of the participants and nonparticipants is significantly higher for technological process innovation (processes for manufacturing goods) than for non-technological process innovation. For technological process innovation the difference is between 86 and 61 per cent. In contrast, for non-technological process innovation the differences are negligible: participants are more likely to introduce new logistics, delivery or distribution processes, but the difference is only 4 percentage points; and only 6 per cent more participants are engaged in introducing new support processes.

Furthermore, participants are more likely to introduce organisational innovation, in both aggregate and disaggregate form. Participants are more innovative in introducing new business practices for organising procedures (58% of participants and 48% of non-participants); in new methods of organising work responsibilities and decision making (47% of participants and 40% of non-participants); and in new methods of organising external relations with other firms or public institutions (52% of participants and 29% of non-participants).

Although participants are more likely to be engaged in marketing innovation than nonparticipants, the difference varies among disaggregated categories of marketing innovation. The highest difference can be observed for the introduction of new methods for sales channels (43 % of participants and 22 % of non-participants), whereas the contrast is less marked for the

[10] Medium size firms have between 50 and 249 employees (one firm with an estimated 250 employees was retained in the database for two reasons: the employment data are respondents' estimates; and this one firm satisfied the turnover criterion for a medium size enterprise); small enterprises have between 10 and 49 employees; and micro enterprises nine or fewer employees.

introduction of new methods of pricing goods or services (29 % of participants and 23 % of non-participants).

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% of participants and 25% 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. Other sectors (Q3t_7) have almost the same proportion of participating and non-participating firms (20% and 21 % respectively).

A significantly higher proportion of participating firms invested fewer resources in innovative activities in the past (Q12t_1) than they do currently (52% of participants and 29% 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 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 (organisational and marketing) innovation, there is no substantial difference in the 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 the export activities (Q5_export), participating firms are slightly more export-oriented (23 per cent) relative to non-participating firms (17 per cent). Participating firms are more prone to collaboration (Q18_yes) than non-participating firms (84% and 33 % 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.

Country dummy variables are included in the model to control for country and regional-specific firm characteristics. Table 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. In our empirical analysis, in almost every estimated model the country dummies for Germany and

Spain turned out to be significant influences on the selection process (participation) but not on the innovation outcome.

Table 2 . Number of participating and non-participating firms by country[11]

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)

Table 3 presents data on innovative firms that have received support measures. The divide between innovative participating and innovative non-participating firms is well balanced; i.e., for each category and sub-category of innovation outcomes, both "operational" (product, process, organisational and marketing innovation) and “economic” (proportions of sales attributed to new or improved products and/or processes), the number of innovative participating firms is around half of the total number of innovative firms. The same proportion holds for the four categories of innovation sales. Therefore, the sample contains similar numbers of participating and non-participating firms in each category of innovation output.

[11] Data in Table 3 are for SMEs only (312 firms in total). There are 21 large firms in the sample.

Table 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 %
Organisational innovation - new business practices for organising procedures	171	51.35 %	85	49.71 %
Organisational innovation - new methods of organising work responsibilities and decision making	142	42.64 %	68	47.89 %
Organisational innovation - new methods of organising external relations with other firms or public institutions	124	37.24 %	75	60.48 %
Organisational 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 %

5. ESTIMATION

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 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). This has two consequences for estimation.

Because the outcome variable, Innovation, can exist in one of two regimes, equation 1 should be estimated for both regimes. This procedure gives the interaction effects of programme selection and all other variables (Lee, 1978), which allows being in one or other regime to affect innovation not only directly but also indirectly by differentially modifying the effects of the other independent variables. Moreover, this is to estimate an unrestricted model, which yields a corresponding efficiency gain (Lokshin and Glinskaya, 2009; Lokshin and Sajaia, 2011). The model defined by equations 1 and 2 restricts the coefficients in the outcome equation to be the same in both regimes. In contrast, by estimating the innovation outcome equation (1) over both regimes 1 and 0, *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).

$$\begin{aligned}
&\text{Regime 1 } (Participation = 1; \text{i.e. participants}):\\
&Innovation_{i1} = \hat{C} + \hat{\beta}_{11}Size_{i1} + \hat{\beta}_{21}MPower_{i1} + \hat{\beta}_{31}Export_{i1}\\
&\qquad + Industry_{I1}\hat{\phi}_{11} + Region_{R1}\hat{\phi}_{21} + Country_{C1}\hat{\phi}_{31}\\
&\qquad + QFFE_{i1}\hat{\alpha}_1 + u_{i1} \qquad (1a)
\end{aligned}$$

$$\begin{aligned}
&\text{Regime 0 } (Participation = 0; \text{i.e. nonparticipants}):\\
&Innovation_{i0} = \hat{C} + \hat{\beta}_{10}Size_{i0} + \hat{\beta}_{20}MPower_{i0} + \hat{\beta}_{30}Export_{i0}\\
&\qquad + Industry_{I0}\hat{\phi}_{10} + Region_{R0}\hat{\phi}_{20} + Country_{C0}\hat{\phi}_{30}\\
&\qquad + QFFE_{i0}\hat{\alpha}_0 + u_{i0} \qquad (1b)
\end{aligned}$$

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). Consequently, we cannot apply standard regression techniques to estimate equations 1a and 1b. Instead, to obtain consistent estimates and standard errors we need to estimate equation 2, equation 1a and equation 1b simultaneously.

In our three equation model, 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 selection equation (ε_i) and the outcome equation in regime 1, (u_{i1}) ρ_1 (rho1);

- between the selection equation (ε_i) and the outcome equation in regime 0, (u_{i0}) ρ_0 (rho0); and
- between 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., 2000, p.31). In this case, the selection process can be treated as exogenous.

The appropriate estimator for our model was developed by Aakvik et al. (2000) and builds on the contribution of James Heckman - one of the co-authors - to the econometric analysis of programme impact. This estimator has been made available to the wider community of applied researchers as a user-written programme for STATA by Lokshin and Sajaia (2011, p.369): "The **switch_probit** command ... implements the full information ML method to simultaneously estimate the binary selection and the binary outcome parts of the model to yield consistent standard errors of the estimates. This approach relies on an assumption of joint normality of the error terms of the estimates."[12]

Given that in this model the effect of *Participation* on *Innovation* is not directly measured in equations 1a and 1b, the question arises as to how we measure the innovation effects of participation in support programmes. This can be done, because the GPrix survey was designed to create a database not only of participants but also of nonparticipants with similar characteristics (other than participation). So, for example, the average number of employees in participating and nonparticipating firms is almost identical (Table 1). Nonparticipating firms form a comparison group. Given a sample of both "treated" (participating) and "comparison" (nonparticipating) firms, 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). Two such statistics are of interest in the present study: the average treatment effect (*ATE*); and the average effect of treatment on the treated (*ATT*).

The average treatment effect (*ATE*) "estimates the effect of a programme on randomly selected persons" (Aakvik et al., 2000, p.12). In the context of our model, the *ATE* is a sample estimate of the effect of programme participation on the innovation of a firm randomly selected from the population. The population concept is

$$ATE \equiv E(y_1 - y_0) \qquad (4)$$

i.e., the expected difference in innovation outcomes with (y_1) and without (y_0) programme participation (Wooldridge, 2002, p.604; Aakvik, 2000, pp.4 and 8). With binary outcomes, the *ATE* is the probability of a firm innovating when participating minus the probability of that firm innovating when not participating in a programme (Aakvik et al., 2000, p.12). However, there is no direct way to apply equation 4. To measure directly the true programme effect would require firms to be observed simultaneously as both participants and nonparticipants. Of course, this is

[12] According to Wooldridge (2009): "Joint MLE is the only reliable method." Readers are referred to the cited papers for the form and derivation of the log-likelihood function, the estimation procedures, and the formulae and derivation of the postestimation statistics. The remainder of the section seeks to provide intuition that will help to interpret the results reported below.

impossible: a firm can be observed in one state or the other but not in both states at the same time. Consequently, *counterfactuals* for y_1 and y_0 have to be constructed from the sample in order to estimate the effect of programme participation indirectly. This requires the unobservable outcomes y_1 and y_0 for the same firms to be estimated from the observed participation and nonparticipation behaviour of different firms in the sample. Accordingly, in our model, *for each firm* the counterfactual outcome for y_1 is a function of the coefficients of the estimated outcome equation for Regime 1 (i.e., predicted innovation for participants);[13] and *for each firm* the counterfactual for y_0 is a function of the coefficients of the estimated outcome equation for Regime 0 (i.e., predicted innovation for nonparticipants).[14] By estimating counterfactuals for y_1 from the "treatment" group (programme participants) and for y_0 from the "comparison" group (nonparticipants), while controlling for both observable and unobservable influences, we can then estimate the treatment effect (*TE*) for each firm in the sample with observed characteristics *x* (Aakvik et al., 2000, p.12; Lokshin and Glinskaya, 2009, p.490):

$$TE(x) = F(X\beta_1) - F(X\beta_o) \qquad (5)$$

TE(x) is the difference between a counterfactual in which all firms in the sample behaved *as if* they were in Regime 1 (i.e., participating in a programme) and a counterfactual in which all firms in the sample behaved *as if* they were in Regime 0 (i.e., not participating). *TE(x)* is averaged across the sample to obtain *ATE*.

The *TT* statistic "estimates the effect of the programme on the entire group of people who participate in it" (Aakvik et al., 2000, p.12) (in the context of our model, "the treated" refers to those firms that participated in support programmes). It is "the expected effect of the treatment on individuals with observed characteristics *x* who participated in the programme" (Lokshin and Sajaia, 2011, p.371; see also Aakvik et al., 2000, p.10) ("observed characteristics *x*" refer to the values of the independent variables in equation 1a). 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).[15] The average treatment effect on participants (*ATT*) is obtained by averaging *TT* over the subsample of participating firms (Lokshin and Glinskaya, 2009).

[13] The product of the data on the independent variables, measuring the observed characteristics of firms, and the estimated intercept and slope coefficients for Regime 1 (see equation 1a) ($X\hat{\beta}_1$); i.e., the linear prediction based on the coefficients of the outcome equation in Regime 1.

[14] The product of the data on the independent variables, measuring the observed characteristics of firms and the estimated intercept and slope coefficients for Regime 0 (see equation 1b) ($X\hat{\beta}_0$); i.e., the linear prediction based on the coefficients of the outcome equation in Regime 0.

[15] The interpretation of equation 7 of Lokshin and Glinskaya (2009, p.490) is particularly tricky. In the context of our model, the treatment on the treated effect for firms with observed characteristics *x* - TT(*x*) - is the difference between the predicted probability that a participating firm will innovate when it is predicted to participate (through equation 2) and the predicted probability that the firm will innovate when not participating *even though it is predicted to participate.* Again, the counterfactuals involve the use of the linear predictions based on the coefficients of the outcome equations for Regime 1 and Regime 0.

6. RESULTS AND DISCUSSION

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 discussed in the previous section, ATE and ATT. Of course, the validity of these postestimation statistics depends on the validity of the regressions that are used to generate the counterfactuals from which they are calculated. Accordingly, we discuss the regression findings briefly, while focussing mainly on the treatment effects.

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, organisational 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) (see Tables 1 and 3 for variable descriptions and descriptive statistics). We do not estimate a model for total innovation (all categories aggregated), because there is little variation in the data (99% of participating firms and 90% of participating firms have undertaken some type of innovation; see Table 1 for TOTAL).

Valid estimation of the model is assisted by the presence of one or more identifying variables.[16] Potentially we have 18 such variables, constructed from Question 31 (see Table 1). Inclusion of all of these variables in equation 2 is precluded by multicollineary and, typically, the lack of a clear maximum to which the likelihood function can converge. Accordingly, preliminary analysis was conducted by means of single equation probit regression to identify those parts of Question 31 that most strongly influenced the selection process (*Participation* in equation 2) while not influencing innovation outcomes (*Innovation* in equations 1a and 1b) on the criterion of Z-statistics of less than one. This identified a provisional list of five potentially strong identifying variables, all of which were included in the full model specification set out in equations 1a, 1b and 2. Typically, the initial fully specified models failed to converge or displayed statistical problems when they did (for example, yielding rho coefficients of one with standard errors of, in effect, zero). Consequently, we undertook a testing down procedure (this is similar to Aakvik et al., 2000, who do not include all variables from their initial specification in their final model; see p.27). Because we begin with a parsimonious model, we were cautious in deleting variables.

The typical results of our testing down procedure were twofold.

1. We reduced the number of Question 31 variables used as instruments to two or three that strongly influenced the selection process (equation 2) but not innovation outcomes (equations 1a and 1b).
2. The country dummies were 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 1. The base (omitted) country is the UK, which has a lower proportion of participants than nonparticipants. Hence, both Germany and Spain with 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 the 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.

[16] There is further discussion of this issue at the end of this section.

The testing down procedure generates a huge quantity of regression output: 20 dependent variables; a testing down procedure from a full model via at least one intermediary stage to the final model; and three tables for each of these 60 (or more) estimations (for equations 1a, 1b and 2). However, the sets of results for the final models have marked similarities and generally only minor differences. All 20 estimated final parsimonious models are reported in full in Appendix 2.[17]

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[18] (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 of significance. The initial conditions have a positive and significant effect on the participation in the 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. Other variables, including export (Q5_export) are not statistically significant. Four identifying variables are included in the model for combined product innovation: two country dummy variables, for Germany and Spain; and indicators for the 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 of the country DVs are statistically significant (Germany at the 5% level and Spain at the 1% 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. Furthermore, the indicator for adequate external assistance and guidance after the project (Q31_17t_5) has a positive and significant impact on programme participation.

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 organisational 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 leather industry (Q3t_1). Finally, exporting firms (Q5_export) are more likely to engage in product innovation (the coefficient is significant at the 5% 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

[17] The full results are all available in log files, available on request from the corresponding author.
[18] Initial conditions - or quasi firm fixed effects - control for firm's innovation capacities at the beginning of the sample period.

likely to innovate. However, leading innovation capabilities in organisational innovation (Q16_4t_1) have a negative impact on product innovation, again, for both participating and non-participating firms.

Turning to the statistical properties of the model, rho1 is negative, which indicates that those firms that are more likely to participate in the support measures are less likely to innovate. However, rho0 is positive and statistically significant, which suggests that non-participating firms are more likely to innovate. The *p* value for the Wald test indicates that the selection and output equations are independent, which further confirms our choice of estimator.

For each model, the estimated coefficients are used to calculate the programme effects ATT and ATE. These estimated effects are presented in Table 4. In addition, we report the correlation coefficients – rho1 and rho2 – from each of our 20 final models, because these are informative about the statistical validity of our estimates. These are generally non-problematic with respect to border values (only one is unity in absolute value with a standard error of zero) and large, although in some cases the associated standard errors are also relatively large. However, following Aakvik et al. (2000, p.32) 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. Moreover, unlike Aakvig et al. (2000, p.32), we find that the Wald test uniformly rejects the null of no selection bias due to unobservables at the 10 per cent level or lower. These are strong results, given that a conservative approach is typically adopted to non-rejection (see also Lokshin and Sajaia, 2011, p.379). In sum, the correlation coefficients and the Wald tests strongly support the validity of our estimation approach.

In Table 1, the raw or unconditional means suggest that both overall and in each separate category of innovation participating firms innovate more than nonparticipating firms. Yet the estimates of ATT and ATE tell a very different story, which suggests the importance of controlling for selection (Aakvik, 2000, p.33). Table 4 presents the preferred models for each dependent variable, in total 20 models. The second column in the Table 4 indicates whether the preferred model is a baseline or an augmented model. The baseline model refers to the model specification that includes only variables common to both the GPrix and the MAPEER database. The augmented model refers to the model specification in which a variable indicating firms' collaboration is added, which arises from a question included in the GPrix survey but not in the MAPEER survey. In each of the 20 cases, the preferred model was chosen according to its statistical characteristics; i.e. the model should not estimate either rho1 or rho0 at the boundary value of unity; and the Wald test should reject the null of the independence of the selection and output equations. Out of 20 models, 13 are baseline models and 7 are augmented models. For all 20 models we followed the rule that if both the baseline and the augmented variants had good statistical characteristics then the baseline model should be chosen as a preferred model.

If we first look at the results for the models where the dependent variables are different types of operational innovation (product, process, organisational and marketing innovations), the ATT effect is smaller than the ATE in almost every case (15 out of 16 models). For ATT 10 from 16 estimates are negative, of which 8 are significantly different from zero. In sum:

- ATT: the mean of the 16 values is -0.06 with a range from -0.43 to 0.27.

In contrast, for ATE 12 from 16 estimates are positive and statistically significant. In sum:

- ATE: the mean of the 16 values is 0.12 with a range from -0.17 to 0.37.

These results suggest that programme participation typically reduced the probability of innovation by programme participants by 6 percentage points but would have increased the probability for firms randomly selected from the entire population by 12 percentage points. Together these results suggest that randomly selected firms benefit more from programme participation than do participants (Aakvik, 2000, pp.3 and 35). This implies that selection of SMEs into support programmes is perverse with respect to innovation outcomes (Aakvik, et al., 2000, p.33).

When the results from the four additional model specifications for categories of innovative sales are included in our review, the results from the models with operational innovation outputs are reinforced. The ATT effect is smaller than the ATE in 18 out of 20 models, with a probability of this result having occurred without a systematic relationship of 0.0002. The results strongly suggest that the effect of support programmes would be more profound if firms were to be randomly chosen to participate in the programmes. Furthermore, a high proportion of the models (9 out of 20) yield a zero or negative ATT and a positive ATE, with a probability of this result having occurred without a systematic relationship of 0.03. These results indicate that on average the impact of support measures on innovation output in the participating firms is at best zero, while the support programmes could have had a positive overall effect on innovation output had the firms been randomly chosen.

There is one discrepancy between the ATT/ATE of support with respect to the 16 innovation categories and with respect to the four categories of “innovation sales”. The ATT effect is smaller than ATE in 15 out of the 16 models of innovation categories. This contrast is replicated in three of the four models of innovation sales (and in the fourth, the difference is negligible). However, only for innovation sales of more than 5 per cent of turnover is the ATT effect both negative and significant while the ATE is positive and significant. In the other two innovation sales models in which ATT is smaller than ATE both effects are positive. In other words, while the dominant pattern is maintained (ATT<ATE) both are shifted in a positive direction in the four models with innovation sales as the dependent variable compared to the 16 with different types of innovation as the dependent variable. This discrepancy between our two measures of innovation output (innovation categories and innovation sales) might result from the different time scales relevant to the two measures.

• The 16 "operational" categories are most likely to be picking up short-term effects, which exclude “behavioural additionality” (in the case of these measures, there is likely to be insufficient time for behavioural changes to have taken place and thus to have had an effect).

• The impact of support measures on “Innovation sales” is likely to take more time to become apparent, so is thus more able to pick up not only the direct effects of programme support but also the indirect effects of behavioural additionality.

The ATT and ATE effects by country are presented in Tables 5 and 6. The overall conclusion is that neither the ATT nor the ATE effects change signs if we compare ATT/ATE across the sample with the individual effects for each country. However, the magnitude and in a few cases the sign of the two effects do differ across countries.

Table 4. Programme participation effects: the average treatment effect on the treated (ATT) and the average treatment effect (ATE) (Bootstrapped standard errors)

Output dependent variable	MODEL	rho1	rho0	Problem with a model?	Wald test (p value)	Average treatment effect on the treated - ATT			Average treatment effect - ATE		
						No of obs.	Coeff.	Bootstr. SEs	No of obs.	Coeff.	Bootstr. SEs
Product innovation in goods	BASELINE	0.300 (0.422)	0.792 (0.159)	NO	0.0713	104	-0.076 ***	0.021	236	0.061 ***	0.019
Product innovation in services	AUGMENTED	-0.751 (0.229)	0.159 (0.474)	NO	0.0257	95	0.272 ***	0.036	215	0.366 ***	0.021
Product innovation - combined	BASELINE	-0.999 (0.004)	0.871 (0.417)	NO	0.0232	108	-0.011	0.018	242	0.118 ***	0.015
Process innovation - processes for manufacturing goods	BASELINE	-0.694 (1.832)	0.754 (0.305)	NO	0.1252	105	-0.046 **	0.020	237	0.180 ***	0.013
Process innovation - logistics, delivery or distribution processes	BASELINE	-0.197 (0.474)	0.829 (0.203)	NO	0.1402	104	-0.426 ***	0.027	243	-0.113 ***	0.017
Process innovation - support processes	BASELINE	-0.046 (0.376)	0.957 (0.059)	NO	0.0305	108	-0.299 ***	0.011	249	-0.097 ***	0.006
Process innovation - combined	BASELINE	-0.406 (0.588)	0.999 (0.002)	NO	0.0183	116	-0.078 ***	0.010	261	0.084 ***	0.010

Organisational innovation - new business practices for organising procedures	AUGMENTED	-0.682 (0.177)	-0.211 (0.332)	NO	0.0293	110	0.144 ***	0.025	245	0.245 ***	0.015
Organisational innovation - new methods of organising work responsibilities	BASELINE	-0.768 (0.284)	0.802 (0.195)	NO	0.0293	113	-0.398 ***	0.023	256	0.082 ***	0.017
Organisational innovation - new methods of organising external relations	AUGMENTED	-0.580 (0.208)	0.034 (0.434)	NO	0.0950	105	0.240 ***	0.023	233	0.347 ***	0.013
Organisational innovation - combined	BASELINE	-0.999 (0.005)	0.655 (0.344)	NO	0.0783	109	-0.140 ***	0.018	243	0.133 ***	0.013
Marketing innovation - changes to design or packaging	BASELINE	0.168 (0.871)	0.872 (0.368)	NO	0.1133	101	-0.385 ***	0.023	235	-0.170 ***	0.014
Marketing innovation - new media or techniques for product promotion	BASELINE	-0.891 (0.166)	0.392 (0.941)	NO	0.0702	102	0.010	0.045	235	0.338 ***	0.023
Marketing innovation - new methods for sales channels	AUGMENTED	-0.384 (0.313)	0.645 (0.533)	Wald test p = 0.2368	0.2368	107	-0.001	0.037	237	0.173 ***	0.022
Marketing innovation - new methods of pricing	BASELINE	-0.611 (0.290)	-0.755 (0.524)	NO	0.0919	113	0.236 ***	0.013	253	0.288 ***	0.012
Marketing innovation - combined	AUGMENTED	0.809 (0.187)	- 0.071 (0.353)	NO	0.0651	109	0.180 ***	0.024	241	-0.002	0.017

Innovative sales > 5 %	BASELINE	-0.488 (1.480)	0.805 (0.157)	NO	0.0902	113	-0.088 ***	0.015	250	0.051 ***	0.011
Innovative sales > 10 %	AUGMENTED	-0.785 (0.479)	0.150 (0.591)	NO	0.0613	110	0.059 ***	0.025	241	0.203 ***	0.016
Innovative sales > 15 %	BASELINE	0.720 (0.414)	0.684 (0.482)	NO	0.1019	112	-0.262 ***	0.019	247	-0.274 ***	0.013
Innovative sales > 25 %	AUGMENTED	-0.521 (0.413)	-0.756 (0.357)	NO	0.0591	110	0.272 ***	0.019	241	0.339 ***	0.013

Significance levels on ATT and ATE: * at 10%; ** at 5%; *** at 1%

Table 5 : The ATT effect by country - preferred models

Variable	OVERALL ATT	Germany	Spain	France	United Kingdom	Italy	Netherlands	Portugal
Product innovation in goods	-0.076 *** (0.021)	-0.201*** (0.052)	0.025 (0.042)	-0.121** (0.047)	-0.064** (0.031)	-0.101* (0.061)	-0.171*** (0.059)	-0.051 (0.040)
Product innovation in services	0.272 *** (0.036)	0.698*** (0.063)	0.467*** (0.041)	0.148 (0.114)	0.074 (0.051)	-0.002 (0.059)	0.416*** (0.095)	-0.290*** (0.051)
Product innovation - combined	-0.011 (0.018)	0.000 (0.006)	0.072** (0.029)	-0.054 (0.059)	0.008** (0.004)	-0.083 (0.073)	-0.078 (0.050)	-0.188* (0.107)
Process innovation - processes for manufacturing goods or providing services	-0.046 ** (0.020)	-0.035 (0.031)	0.052 (0.035)	-0.139 (0.103)	-0.108*** (0.034)	-0.004 (0.048)	-0.205*** (0.055)	-0.107 (0.077)
Process innovation - logistics, delivery or distribution processes	-0.426 *** (0.027)	-0.524*** (0.052)	-0.162*** (0.034)	-0.547*** (0.049)	-0.536*** (0.055)	-0.581*** (0.061)	-0.468*** (0.085)	-0.698*** (0.071)
Process innovation - support processes (e.g. maintenance, purchasing, accounting etc.)	-0.299 *** (0.011)	-0.288*** (0.031)	-0.302*** (0.019)	-0.299*** (0.035)	-0.276*** (0.022)	-0.346*** (0.032)	-0.302*** (0.032)	-0.249*** (0.053)
Process innovation - combined	-0.078 *** (0.010)	-0.100*** (0.022)	-0.011 (0.012)	-0.108*** (0.019)	-0.097*** (0.026)	-0.085*** (0.025)	-0.165*** (0.033)	-0.099** (0.048)
Organisational innovation - new business practices for organising procedures	0.144 *** (0.025)	0.051 (0.052)	0.272*** (0.040)	-0.043 (0.101)	0.089* (0.050)	0.226*** (0.060)	0.040 (0.088)	0.114 (0.070)
Organisational innovation - new methods of organising work responsibilities and decision making	-0.398 *** (0.023)	-0.625*** (0.038)	-0.234*** (0.029)	-0.474*** (0.075)	-0.407*** (0.045)	-0.361*** (0.048)	-0.527*** (0.065)	-0.390*** (0.098)
Organisational innovation - new methods of organising external relations with other firms or public institutions	0.240 *** (0.023)	0.316*** (0.066)	0.312*** (0.035)	0.161* (0.084)	0.172*** (0.060)	0.171*** (0.063)	0.158** (0.070)	0.347*** (0.117)
Organisational innovation - combined	-0.140 *** (0.018)	-0.224*** (0.060)	-0.092*** (0.031)	-0.234*** (0.083)	-0.184*** (0.036)	-0.056 (0.049)	-0.114*** (0.035)	-0.190*** (0.053)

Marketing innovation - changes to aesthetic design or packaging	-0.385 *** (0.023)	-0.567*** (0.034)	-0.214*** (0.033)	-0.262*** (0.063)	-0.488*** (0.050)	-0.459*** (0.050)	-0.470*** (0.059)	-0.244*** (0.083)
Marketing innovation - new media or techniques for product promotion	0.010 (0.045)	0.512*** (0.070)	0.217*** (0.050)	-0.280 (0.173)	-0.132* (0.069)	-0.447*** (0.077)	-0.060 (0.121)	0.117 (0.208)
Marketing innovation - new methods for sales channels	-0.001 (0.037)	0.097 (0.063)	0.087 (0.066)	-0.216*** (0.079)	-0.111 (0.076)	-0.076 (0.080)	0.020 (0.138)	0.250 (0.208)
Marketing innovation - new methods of pricing goods or services	0.236 *** (0.013)	0.306*** (0.027)	0.287*** (0.018)	-0.082** (0.037)	0.242*** (0.027)	0.196*** (0.022)	0.234*** (0.029)	0.325*** (0.055)
Marketing innovation - combined	0.180 *** (0.024)	0.153*** (0.052)	0.280*** (0.049)	0.146* (0.076)	0.131** (0.056)	0.137** (0.068)	0.128 (0.080)	0.173*** (0.065)
Innovative sales > 5 %	-0.088 *** (0.015)	-0.251*** (0.053)	-0.089** (0.035)	0.027 (0.020)	-0.053** (0.022)	-0.043** (0.017)	-0.090** (0.038)	-0.126* (0.067)
Innovative sales > 10 %	0.059*** (0.025)	0.080* (0.045)	0.105* (0.055)	0.004 (0.116)	-0.046 (0.048)	0.129** (0.055)	0.038 (0.070)	0.111 (0.136)
Innovative sales > 15 %	-0.262 *** (0.019)	-0.171*** (0.057)	-0.323*** (0.041)	-0.187*** (0.046)	-0.245*** (0.040)	-0.282*** (0.035)	-0.264*** (0.050)	-0.286*** (0.079)
Innovative sales > 25 %	0.272 *** (0.019)	0.206*** (0.033)	0.171*** (0.021)	0.439*** (0.077)	0.386*** (0.055)	0.264*** (0.029)	0.284*** (0.032)	0.238*** (0.057)

Significance levels on ATT: * at 10%; ** at 5%; *** at 1%

Table 6: The ATE effect by country - preferred models

Variable	OVERALL ATE	Germany	Spain	France	United Kingdom	Italy	Netherlands	Portugal
Product innovation in goods	0.061 *** (0.019)	-0.036 (0.065)	0.126*** (0.038)	-0.008 (0.089)	0.038 (0.033)	0.085* (0.044)	0.086* (0.050)	0.096 (0.070)
Product innovation in services	0.366 *** (0.021)	0.769*** (0.034)	0.532*** (0.031)	0.148*** (0.073)	0.237*** (0.029)	0.269*** (0.041)	0.560*** (0.045)	-0.116 (0.084)
Product innovation - combined	0.118 *** (0.015)	0.076 (0.057)	0.174*** (0.027)	0.128*** (0.039)	0.118*** (0.028)	0.101** (0.047)	0.098** (0.042)	0.084 (0.060)
Process innovation - processes for manufacturing goods or providing services	0.180 *** (0.013)	0.181*** (0.043)	0.166*** (0.030)	0.165** (0.064)	0.159*** (0.025)	0.251*** (0.031)	0.163*** (0.040)	0.166*** (0.043)
Process innovation - logistics, delivery or distribution processes	-0.113 *** (0.017)	-0.351*** (0.053)	0.053*** (0.028)	-0.188*** (0.048)	-0.133*** (0.032)	-0.092** (0.046)	-0.056 (0.058)	-0.196*** (0.066)
Process innovation - support processes (e.g. maintenance, purchasing, accounting etc.)	-0.097 *** (0.006)	-0.079*** (0.011)	-0.111*** (0.018)	-0.107*** (0.028)	-0.115*** (0.011)	-0.065*** (0.016)	-0.090*** (0.020)	-0.085*** (0.016)
Process innovation - combined	0.084 *** (0.010)	-0.051* (0.027)	0.105*** (0.016)	0.088** (0.034)	0.073*** (0.018)	-0.132*** (0.025)	0.065* (0.039)	0.022 (0.025)
Organisational innovation - new business practices for organising procedures	0.245 *** (0.015)	0.202*** (0.040)	0.315*** (0.030)	0.099* (0.058)	0.279*** (0.030)	0.300*** (0.038)	0.160*** (0.052)	0.106 (0.065)
Organisational innovation - new methods of organising work responsibilities and decision making	0.082 *** (0.017)	-0.236*** (0.041)	0.091*** (0.029)	0.094 (0.057)	0.137*** (0.031)	0.230*** (0.036)	0.094* (0.055)	-0.058 (0.046)
Organisational innovation - new methods of organising external relations with other firms or public institutions	0.347*** (0.013)	0.430*** (0.030)	0.351*** (0.028)	0.236*** (0.044)	0.303*** (0.025)	0.376*** (0.025)	0.363*** (0.035)	0.453*** (0.046)
Organisational innovation - combined	0.133 *** (0.013)	0.070** (0.026)	0.087*** (0.024)	0.099* (0.060)	0.134*** (0.022)	0.250*** (0.030)	0.203*** (0.040)	-0.060*** (0.018)

Marketing innovation - changes to aesthetic design or packaging	-0.170 *** (0.014)	-0.322*** (0.035)	-0.074** (0.030)	-0.135** (0.053)	-0.263*** (0.021)	-0.094*** (0.030)	-0.153*** (0.049)	-0.066 (0.046)
Marketing innovation - new media or techniques for product promotion	0.338 *** (0.023)	0.668*** (0.035)	0.413*** (0.049)	0.216** (0.081)	0.324*** (0.039)	0.078 (0.050)	0.473*** (0.064)	0.321*** (0.074)
Marketing innovation - new methods for sales channels	0.173 *** (0.022)	0.188*** (0.051)	0.145*** (0.049)	0.043 (0.056)	0.203*** (0.037)	0.127*** (0.047)	0.162** (0.072)	0.443*** (0.102)
Marketing innovation - new methods of pricing goods or services	0.288 *** (0.012)	0.360*** (0.013)	0.308*** (0.013)	-0.234*** (0.043)	0.315*** (0.013)	0.329*** (0.015)	0.353*** (0.020)	0.427*** (0.037)
Marketing innovation - combined	-0.002 (0.017)	-0.017 (0.038)	0.190*** (0.042)	-0.042 (0.053)	-0.064** (0.029)	-0.087** (0.036)	-0.056 (0.055)	0.128 (0.080)
Innovative sales > 5 %	0.051*** (0.011)	-0.185*** (0.041)	0.089*** (0.023)	0.109*** (0.029)	0.065*** (0.015)	0.142*** (0.026)	0.055** (0.026)	-0.063 (0.042)
Innovative sales > 10 %	0.203 *** (0.016)	0.172*** (0.053)	0.155*** (0.040)	0.240*** (0.048)	0.189*** (0.028)	0.269*** (0.047)	0.190*** (0.043)	0.246*** (0.069)
Innovative sales > 15 %	-0.274 *** (0.013)	-0.201*** (0.038)	-0.262*** (0.029)	-0.206*** (0.044)	-0.266*** (0.028)	-0.303*** (0.027)	-0.351*** (0.033)	-0.340*** (0.050)
Innovative sales > 25 %	0.339 *** (0.013)	0.240*** (0.028)	0.222*** (0.019)	0.487*** (0.049)	0.440*** (0.031)	0.331*** (0.023)	0.304*** (0.024)	0.282*** (0.046)

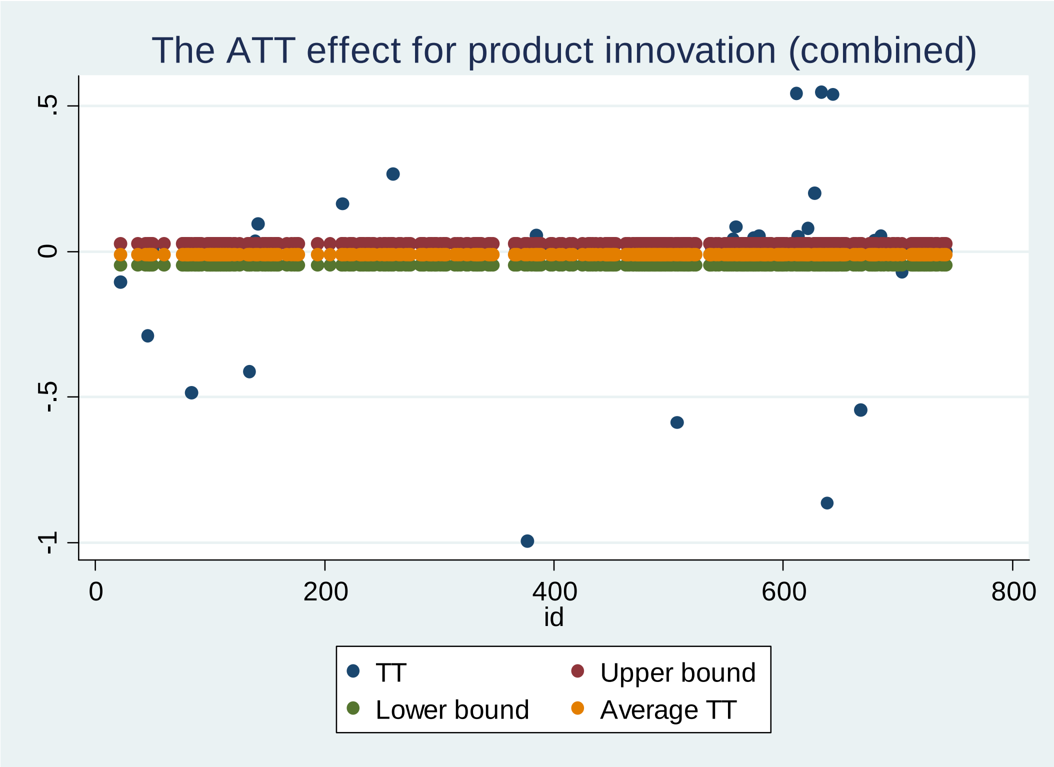
Significance levels on ATE: * at 10%; ** at 5%; *** at 1%

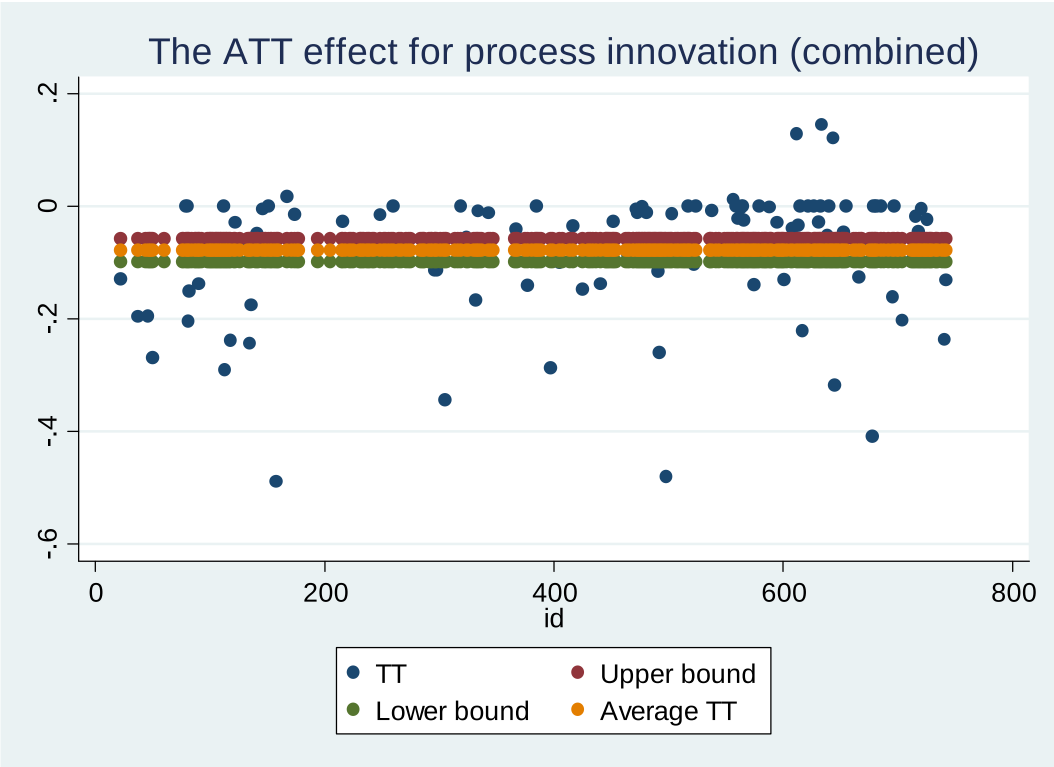
If the selection process into support programmes were independent of the innovation outcomes, such that programme participation were random across firms, then the ATT and the ATE would be identical in each case (Wooldridge, 2002, pp.605-06). Hence, the systematic difference in our results between the ATT and the ATE estimates suggests that the selection process modelled by the *Participation* variable is not random; instead, selection by programme managers and/or self-selection by firms is dependent on observed and/or unobserved firm characteristics. This evidence is consistent with our assumption that the selection process is potentially endogenous.

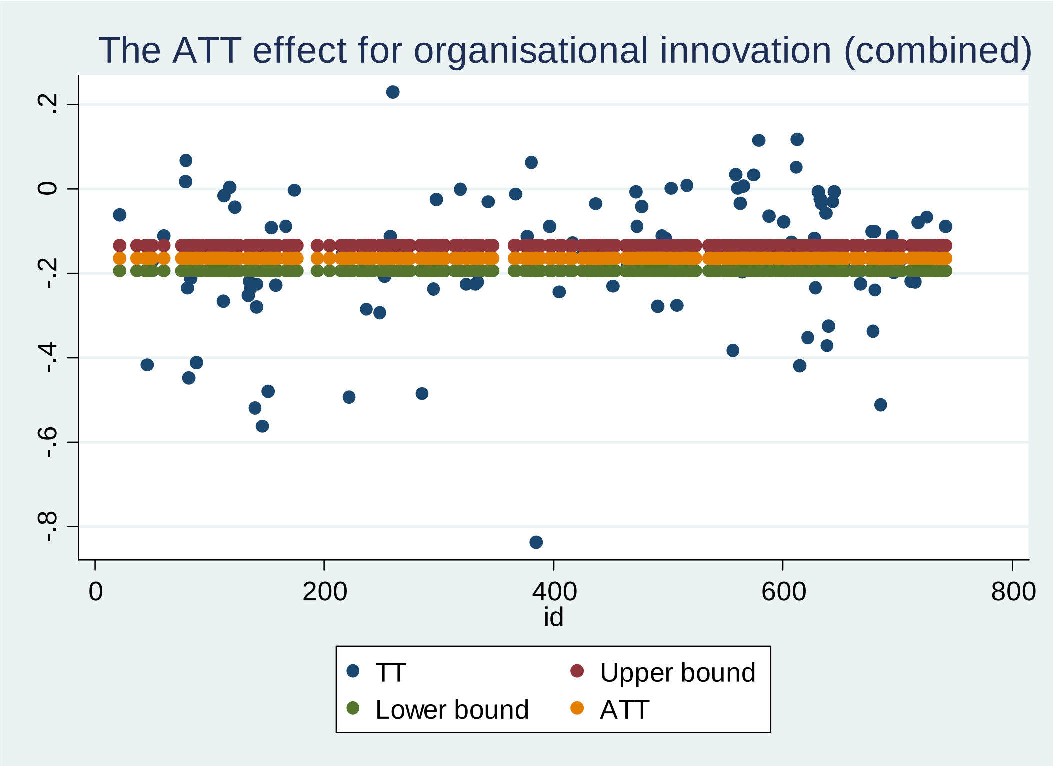
To study the relationship between unobservable characteristics related to programme participation and the treatment effects, we interpret the correlation coefficients, rho1 and rho0 (Aakvik et al., 2000, pp.33 and 36-37). In 13 of the 20 final models, rho1 is negative and rho0 is positive; in three, both rho1 and rho0 are negative; in three, 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 product innovation in services, the correlation between the unobservables from the selection equation and the unobservables from the output equation for participants (rho1) is -0.751, while the correlation between the unobservables from the selection equation and the output equation for non-participation (rho0) is 0.159. 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 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 that are more likely to participate in the support programme are less likely to innovate relative to a random firm from the sample, whereas firms that are least 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 the lowest for the firms that are more likely to participate in the programmes. As Aakvik et al. (2000, p. 37) 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”. This pattern of residuals (negative rho1 and positive rho0) is the dominant pattern in our findings and the implication of “perverse selection” is consistent with the characteristic contrast between a smaller ATT and a larger ATE identified above.

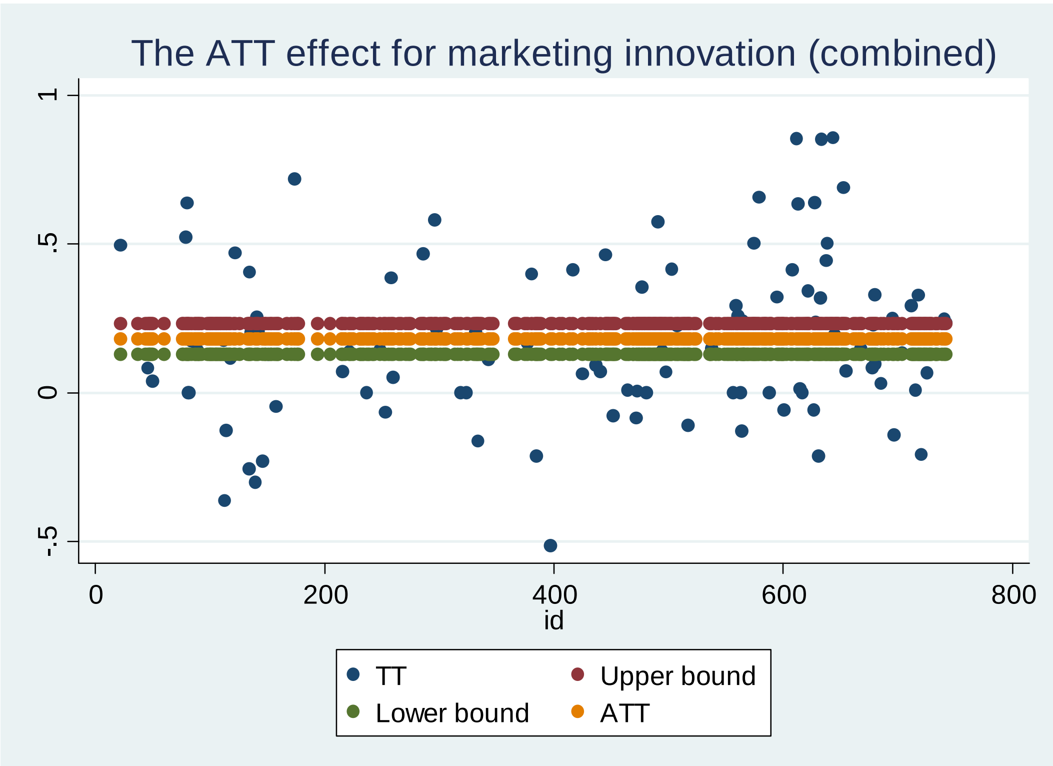
In Figure 1, we present the distribution of the estimated effects of participation in support measures programme participation on the probability that participants will innovate (i.e. the TT - treatment effect on the treated). For each participant, we plot the TT for aggregate product, process, organisational and marketing innovation. In addition, each chart displays the average effect on participants (ATT) together with an upper bound (the ATT plus two standard errors) and a lower band (the ATT minus two standard errors). This demonstrates that although for most firms programme participation yields little or no discernable innovation output, for many firms there is a large positive effect and for many a large negative effect. Hence, our econometric analysis is consistent with the success stories typically written up as case studies to demonstrate to other SMEs the potential benefits of participation and to demonstrate to policy makers a return on public funds. However, while such success stories are undoubtably genuine, they are a selection from a selection. Firms are ex ante “cherry picked” into support programmes; and then, ex post, participating firms are subject to further “cherry picking” to identify success stories.

Figure 1. Distribution of the innovation effects of programme participation on participants – estimated effect on the probability of innovation for each programme participant (TT = treatment on the treated effects)









Lower bound = ATE – 2 standard errors
Upper bound = ATE + 2 standard errors

Finally, we consider two 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 organisation that capitalist enterprise creates ... that incessantly revolutionises 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).

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). Conversely, specification where the error terms are nonnormally 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 errors are $\chi 2$ distributed and 'simulation based on different functional forms for the nonnormal 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.

7. CONCLUSIONS AND POLICY IMPLICATIONS

In the absence of randomised experiments to evaluate innovation support for SMEs in traditional manufacturing industries, to identify the effect of programme participation requires not only a comparison group to control for innovation by non-participants but also a model to estimate the effects of programme participation beyond the effects of selection bias. These best practice requirements are demonstrated by the contrast between the raw descriptive statistics for innovation by participants and nonparticipants and the estimated treatment effects reported and discussed in the previous section. Best practice in the evaluation of innovation support programmes requires moving beyond gross differences between participants and non-participants to estimates of programme effects that are net of – i.e. beyond - the effects of differences in both the observed and the unobserved characteristics of participants and non-participants.

In our study, the gross effects are most misleading if interpreted as indicating causal effects of programme participation on firms' innovation behaviour. In the context of a population of mainly innovating SMEs, our estimated programme effects – ATT and ATE - suggest that support programmes have a zero or even slightly negative effect on the innovation of SME participants but a positive effect on randomly selected SMEs. Moreover, consistent with this finding, analysis of the unobserved effects captured by our model suggest that the more likely a firm is to participate in a support programme the less likely that firm is to innovate *as a consequence*. Conversely, firms that are less likely to participate would be more likely to innovate *as a consequence* (i.e. were they to participate).[19] In relation to the wider literature on programme effects, reviewed in Section 2 above, the evidence of the estimated ATT effects reported in this study is consistent with those previous investigations that find no evidence of additionality or even of a small crowding out effect.

These results are consistent with evidence from interviews with programme managers in all seven EU regions covered by the GPrix project as well as with both published and unpublished documentary sources (which were generously shared with the project team). Namely, the selection procedure adopted by programme managers is typically one of extreme "cream skimming" or "cherry picking"; in other words, firms are selected for programme participation on the basis of observed characteristics that are positively associated with innovation. The firms selected for innovation support are those most likely to innovate irrespective of programme support. The reasons for this selection strategy are two-fold, involving both incentive and scope to "cream skim".

- The first is similar to that identified by Aakvig et al. (2000, p.45): 'Governmental evaluations of training programs in most countries typically are based on post-program outcome measures. Such an evaluation strategy gives caseworkers an incentive to select the most employable for training.'
- The second is that there are many obstacles – notably bureaucratic – to SME participation in support programmes. These are well documented by the GPrix project as well as by other projects. When the result of these is lack of interest by SMEs in support programmes, programme managers and case workers are forced to actively recruit which, in turn, gives more scope to "cream skim".

Yet the consequences of a "cream skimming" selection strategy are perverse. Raw means of innovation by participants and nonparticipants will overstate the effects of participation. Indeed, the raw means may indicate positive effects where the true impact is zero or even negative. Our results suggest that cream-skimming of firms on the basis of characteristics

[19] These findings are similar to the canonical study by Aakvik et al. (2000, p.40) who also find that 'those most likely to participate in the program are those who benefit least from it'.

positively associated with innovation is less effective in promoting innovation than randomly selecting participants (Aakvig et al., 2000, pp.44-45).

These findings have direct implications for policy makers.

1. ***Best practice evaluation should be required for all major innovation support programmes***. As Aakvik et al. (2000, p.45) note in relation to training programmes: "Caseworkers are seldom able to estimate treatment effects. Thus guidance on who should participate should be based on results from research rather than by rules-of-thumb." Even where consultants are engaged to evaluate programmes, the evidence from the GPrix research is that evaluation is never conducted according to best practice guidelines. Sometimes, this is the fault of consultants who either do not know of best practice or, when they do, ignore it. Conversely, when consultants suggest best practice evaluation – in particular, the use of a comparison group – lack of knowledge on the part of programme managers can make them disinclined to incur the expense of sound evaluation. Accordingly, while endorsing the general advice of Aakvik (2000), to spread best practice evaluation, to do so will require several more supporting reforms:
    a. the cost of evaluation should be built into programme budgets;
    b. evaluation design should inform data gathering before, during and after programme participation; and
    c. training should be required to raise the awareness of programme managers of best practice evaluation so that they can better specify requirements when commissioning evaluation and assess the quality of subsequent evaluation reports (this recommendation is consistent with OECD, 2007, p.29).

2. ***The selection process of firms into innovation support programmes should be reformed***. 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.[20] Of course, some transparent criteria for participation – thus some continued selection on observables - will still be needed to ensure that participating firms meet minimum thresholds for benefitting from support programmes (for example, by screening out "hobby" or "life-style" businesses). If this can be achieved then movement from cream-skimming towards a more – but not completely - inclusive selection process should enhance the effectiveness of innovation support programmes for SMEs in traditional manufacturing industries.

3. To reform the selection process by making it more inclusive requires many more firms to select from. Without greater awareness on the part of SMEs and correspondingly higher levels of interest, programme managers will continue to have to target and recruit firms in order to spend their programme budgets. Consequently, ***a corollary of moving away from cream-skimming is the need to remove participation obstacles***; in particular, by making application, selection and reporting procedures less bureaucratic. Increasing the number of firms wanting to participate in innovation support programmes will increase the scope for reforming the selection process in favour of typical rather than special SMEs.

In addition, the findings of this evaluation are consistent with another GPrix policy recommendation; namely, to ***simplify and broaden the scope of Research and Development***

[20] Again, reflecting similar results, this echoes a conclusion from Aakvig et al. (2000, p.45): '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.'

(R&D) tax credits. Greater emphasis on innovation support through the tax system will reduce the prevalence of "cherry picking" firms for support. In turn, the GPrix evaluation suggests that by supporting all eligible firms, programme effectiveness will be enhanced (i.e. additionality increased).

In many EU countries R&D tax credits are by far the largest innovation support programme (e.g. in the UK amounting to £1 billion in 2009-10). Yet R&D tax credits are not easily compatible with the innovation models of SMEs in traditional manufacturing industry. Both the GPrix questionnaire survey and the GPrix case studies support other research in finding that few such firms have R&D departments or even undertake R&D in a sufficiently narrow sense to qualify for tax credits. Instead, their innovation models are based on design, especially technical design, as well as on tacit knowledge and advanced craft skills. Accordingly, to help SMEs in traditional sectors, R&D tax credits should be reformed in two ways:

1. broaden eligibility to include innovation by design (especially technical design) and marketing activities (especially exporting); and
2. simplify application procedures to increase SME take up.

In effect, the proposal is to transform the R&D tax credit – arguably the product of an outmoded, technical and narrow model of innovation – into ***an innovation tax credit more in tune with a broader concept of innovation,*** which includes both technological and non-technological innovation.

The proposal for a broader innovation tax credit to replace or supplement R&D tax credit is consistent with other principles and recommendations supported by GPrix research into innovation and innovation support for traditional sector SMEs. In brief, these are as follows.

1. Broaden the scope of innovation support measures to match the innovation models of SMEs in traditional sectors.
2. Favour demand-led support which, in turn, has the advantage of being market-led rather than bureaucratically-led.
3. Simplify innovation support for SMEs; fund fewer and more stable programmes. In turn, reducing the number of support programmes is more likely to increase take-up by SMEs if two further GPrix recommendations were to be implemented:
    a. long-term institutional stability of the innovation tax credit, facilitating recognition, trust and investment in the fixed costs of application; and
    b. advice and practical assistance in making applications, especially for first-time applicants.
4. An innovation tax credit would end discrimination against enterprises that belong to groups and so, although operating much like SMEs in an economic sense, do not satisfy legal definitions for participation in many SME support programmes.

Finally, to these principles and recommendations the GPrix evaluation adds a value for money argument for innovation support delivered through tax credits.

Finally, this study has a number of novel features but also some limitations. Novel or at least unusual features include: focus on the effectiveness of public innovation support programmes for small and medium enterprises (SMEs) in traditional manufacturing industries; focus on output additionality in relation to a broad range of innovation outputs (both technological and non-technological); drawing on complementary qualitative research, in particular to gain insight into "cream skimming" selection procedures for support programmes; prepublication of the model to be estimated, thereby eliminating bias from subsequent specification search and reducing the need for robustness checks; within the framework of an endogenous switching model we introduce *firm level 'quasi' fixed effects* (or initial conditions) to substitute for *most* firm and ownership effects on innovation; survey questions designed to generate the variables defined by the model; and survey data gathered specifically to address the research hypothesis.

There are two 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. Moreover, some insight is gained into the cumulating of effects by comparison of programme participation effects on innovation outcomes that are "operational", and so likely to occur quickly if they are to occur at all, and participation effects on innovation outcomes that are "economic" and so become apparent only over time, if they occur at all. While the dominant pattern across all our estimates is that ATT<ATE, both are shifted in a positive direction in the four models with "economic" outcomes (innovation sales) as the dependent variable compared to the 16 with different types of "operational" innovation as the dependent variable. This is consistent with the indirect effects of behavioural additionality working over time. The second limitation is that we cannot test the distributional assumption of the estimator used in this study. However, as we argue at the end of the previous section, the evidence on the effects of the failure of this assumption 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). This finding suggests that a more inclusive selection procedure could improve the effectiveness of innovation support programmes for SMEs in traditional manufacturing industry.

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Appendix 1: a model to evaluate the impact of programme participation and the corresponding survey questions

These questions were developed to be included not only in the GPrix questionnaire survey but also in the questionnaire of a project running alongside and complementary to GPrix. By coordinating a subset of their survey questions, GPrix and MAPEER will be able to combine part of their datasets to create a unique resource for quantitative evaluation of innovation support programmes throughout the European Union. Accordingly, Appendix 1 details the GPrix questions but also notes the corresponding MAPEER survey questions.

Where possible, questions were adopted or adapted from established sources (such as the *Community Innovation Survey*); where necessary, new ones were devised.

Some questions do not translate directly into a variable in the model; in some cases the variables have to be derived (for example, by combining categories to form a binary indicator or dummy variable).

Variables:		Questions: **Number of the Question in the GPrix questionnaire;** **& (Equivalent question in the MAPEER on-line questionnaire)**
• **Variables of interest**		
1.	The effect of innovation on firm performance (e.g., innovation activities, turnover and/or employment) (*Innovation*)	Qu.7. Product innovation: From 2005 to 2009 did your company introduce any new or significantly improved … goods; service? • No equivalent question in the MAPEER survey Qu.8. Process innovation: From 2005 to 2009 did your company introduce any new or significantly improved … ? (See Table 1 for the three categories of process innovation.) • No equivalent question in the MAPEER survey Qu.9. Organisational innovation: From 2005 to 2009 did your company introduce …? (See Table 1 for the three categories of organisational innovation.) • No equivalent question in the MAPEER survey Qu.10. Marketing innovation: From 2005 to 2009 did your company introduce …? (See Table 1 for the four categories of marketing innovation.) • No equivalent question in the MAPEER survey Qu.14. How many job positions have been created sustained or lost in your company as a result of introducing new or substantially improved products or processes since 2005? (cf. MAPEER #15) Qu.17. What proportion of your current sales by value comes from new or substantially improved products or processes introduced since 2005? (cf. MAPEER #14)

2.	Programme participation indicator(s) (*Participation*)	Qu.20a. Did your enterprise during the five years 2005 to 2009 receive any public financial support for your innovation activities from the following levels of government? Qu.21. From how many different support measures did you receive support? Qu.22. If possible, please name up to 2 public support measures which have been most important in supporting your innovation activities. Qu.23. For which of the following innovation activities have you used the support received through [PSM1]? (cf. MAPEER #33, #34, #35, #36, #37) • Q.27 repeats the same question for PSM2 Qu.24. For [PSM1] which were the impacts from your participation on ...? (cf. MAPEER #33, #34, #35, #36, #37) • Q.28 repeats the same question for PSM2 Qu.25. Please estimate in Euros/Pounds the amount your enterprise has received in support from [PSM1] • Q.29 repeats the same question for PSM2 Qu.26. Would you have taken the same or similar steps without this public support? • Q.30 repeats the same question for PSM2
3.	One variable to measure the effect of innovation on the ability of firms to cope with the current recession (*Recession_Impact*)	Qu.13. What has been the impact of the recession on your company in relation to: Orders for new and improved products; Orders for established products (cf. MAPEER #20)

	• **Participation variable(s)**	
4.	One or more identifying variables: could be some obstacle to participation in support programmes (*Obstacle*)	Qu.31. Which of the following would you say are the specific needs by all SMEs to enable them to participate in innovation support programmes? (cf. MAPEER #53, #54, #55, #56)
	• **Control variables**	
5.	Firm's (*Size*)	Qu.1. What was your enterprise's total turnover for 2005 and 2009? (cf. MAPEER #6) Qu.2. What was your enterprise's total number of employees in 2005 and 2009? (cf. MAPEER #7, #8)
6.	Firm's market power (*MPower*)	Qu.4. How would you judge the competition in your main market(s)? (cf. MAPEER #10)
7.	Firms' exporting (*Export*)	Qu.5 What was the estimated share of total sales of your firm in 2009 sold to … the same region (e.g. the West Midlands), the rest of the country (e.g. the UK), other European countries, and the rest of the world (cf. MAPEER #11)
8.	Industry fixed effects (dummy variables) (*Industry*)	Qu.3b. In which of the following sectors is your main activity? (cf. MAPEER #9)
9.	Regional fixed effect (*Region*)	Name of enterprise: ____________________ Address: ____________________ ZIP/Postal code: ____________________
10.	Country fixed effects (dummy variables) (*Country*)	
11.	A quasi firm fixed effect - or initial condition; i.e., a pre-sample variable to control for the 'permanent' capacity of the firm to innovate (*QFFE*)	Qu.12. Five years ago did you devote: Fewer resources to innovation; About the same resources to innovation; More resources to innovation Qu.16. How would you judge your firm's innovation capabilities within your industry in the past and now, regarding … Product innovation, Process innovation, Organisational innovation, and Marketing innovation? (asked separately for 2005 and 2009) (cf. MAPEER #18)

Appendix 2: Results for each empirical model

Variable in the dataset	Product innovation in goods						Product innovation in services						Product innovation - combined					
	Participation in support programme		Non-participation in support programme		Selection decision		Participation in support programme		Non-participation in support programme		Selection decision		Participation in support programme		Non-participation in support programme		Selection decision	
	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error
Q2_2009	0.003	0.004	0.005 *	0.003	-0.001	0.002	0.002	0.003	-0.001	0.004	-0.001	0.003	0.042	0.052	0.001	0.003	-0.001	0.002
Q4t_5	0.827*	0.486	-0.556 **	0.280	-0.026	0.213	-0.775**	0.376	-0.634*	0.368	0.368	0.276	-5.164***	0.707	-0.714	0.447	-0.090	0.265
Q3t_1	5.742***	0.811	-0.286	0.526	0.056	0.460	-6.895***	1.909	-1.648**	0.693	0.189	0.601	2.913	1.825	-0.771	0.529	0.012	0.494
Q3t_2	-0.224	0.618	0.962*	0.550	-0.119	0.424	0.793	0.714	0.016	0.714	-0.579	0.447	14.541***	1.947	1.008	0.714	-0.224	0.466
Q3t_3	6.304***	0.609	0.490	0.426	-0.022	0.345	0.727	0.657	-0.861	0.534	-0.534	0.484	14.800***	1.164	0.246	0.504	-0.127	0.356
Q3t_4	0.286	0.457	0.827**	0.387	0.393	0.271	-0.003	0.393	-0.343	0.450	0.236	0.312	9.223***	1.269	0.684	0.484	0.286	0.291
Q3t_5	0.426	0.610	0.114	0.418	-0.176	0.360	0.534	0.668	-0.138	0.531	-0.018	0.483	9.852***	1.190	0.340	0.524	-0.081	0.357
Q3t_6	1.028	0.635	0.783**	0.389	0.438	0.337	-0.085	0.434	-1.489***	0.558	-0.958	0.401	12.382***	1.763	0.544	0.521	-0.553*	0.373
Netherlands							-0.032	0.411	-1.294 **	0.578	0.222	0.381						
Portugal							0.316	0.558	1.732 **	0.734	-0.425	0.543						
France											1.226**	0.512						
Germany					0.634*	0.328	0.234	0.472	-7.449 ***	0.376	0.221	0.365					0.721**	0.296
Spain					1.340***	0.259					1.769***	0.479					1.427***	0.257
Q12t_1	-0.199	0.415	0.716***	0.262	0.728	0.182	-0.198	0.317	0.394	0.343	0.677***	0.246	-0.623	1.301	0.877***	0.288	0.703***	0.179
Prodin_2005	-0.197	0.440	1.028***	0.374	-0.175	0.254	-0.463	0.408	-0.235	0.413	-0.317	0.282	9.046***	0.792	1.175**	0.536	-0.173	0.254
Procin_2005	1.154*	0.628	-0.415	0.381	0.359	0.271	0.446	0.429	0.547	0.444	0.056	0.312	8.858***	0.792	-0.499	0.543	0.377	0.260
Q16_3t_1	-0.594	0.425	-0.244	0.330	0.087	0.248	0.153	0.336	0.446	0.418	-0.070	0.311	-0.540	1.155	-0.021	0.306	0.082	0.238
Q16_4t_1	0.035	0.432	-0.223	0.317	-0.049	0.251	-0.542	0.373	-1.192**	0.463	0.234	0.312	-4.023***	1.463	-0.549*	0.309	-0.080	0.247
Q5_export	0.014 **	0.007	-0.003	0.005	0.003	0.003	-0.012**	0.005	-0.001	0.006	0.002	0.004	0.117 **	0.058	0.003	0.005	0.003	0.003
Q18_yes											1.928 ***	0.294						
Q31_3t_5											0.810 ***	0.279						
Q31_7t_5											-0.913 ***	0.321						
Q31_10t_5											0.577 *	0.322						
Q31_17t_5					0.792**	0.315					0.972 ***	0.356					0.783 **	0.380
Q31_18t_5					-0.407	0.259											-0.332	0.281
Log likelihood	-238.11057						-185.24208						-205.85905					
No of obs.	236						215						242					
rho1	0.300 (0.442)						-0.751 (0.229)						-0.999 (0.005)					
rho0	0.792 (0.159)						-0.159 (0.474)						0.871 (0.417)					
Wald test	p = 0.0713						p = 0.0257						p = 0.0232					

Variable in the dataset	Process innovation - Processes for manufacturing goods or providing services						Process innovation - Logistics, delivery or distribution processes						Process innovation - Support processes (maintenance, purchasing, accounting etc.)					
	Participation in support programme		Non-participation in support programme		Selection decision		Participation in support programme		Non-participation in support programme		Selection decision		Participation in support programme		Non-participation in support programme		Selection decision	
	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error
Q2_2009	0.004	0.005	0.003	0.003	-0.000	0.002	0.006**	0.003	0.004	0.003	-0.001	0.002	0.004	0.003	0.009**	0.004	-0.001	0.002
Q4t_5	-0.272	0.413	-0.616**	0.276	-0.011	0.222	-0.079	0.364	0.262	0.256	-0.035	0.210	0.014	0.336	-0.290	0.261	-0.033	0.209
Q3t_1	6.383***	1.852	0.420	0.658	-0.018	0.519	-0.580	0.831	-0.261	0.539	-0.061	0.468	-0.992	0.959	-1.749***	0.485	-0.105	0.445
Q3t_2	-0.650	0.625	0.938*	0.565	-0.062	0.496	-0.436	0.566	0.485	0.481	-0.155	0.411	-0.382	0.529	0.063	0.481	-0.252	0.404
Q3t_3	0.018	0.973	0.470	0.453	-0.305	0.371	-0.492	0.491	-0.050	0.378	-0.102	0.333	0.169	0.538	0.030	0.361	-0.165	0.314
Q3t_4	0.703	1.112	0.660**	0.329	-0.288	0.325	-1.269 ***	0.432	0.144	0.301	0.196	0.253	0.072	0.379	-0.127	0.303	0.392	0.245
Q3t_5	-0.004	0.555	0.372	0.429	-0.141	0.399	-1.230**	0.574	0.055	0.375	-0.234	0.337	-0.098	0.645	-0.145	0.370	-0.302	0.346
Q3t_6	6.658***	1.488	1.140	0.429	-0.609*	0.358	-0.296	0.444	0.100	0.374	-0.536*	0.310	-0.232	0.421	-0.291	0.360	-0.534	0.344
Germany					0.548	0.352	0.743	0.468			0.554*	0.319						
France																	0.548**	0.269
Spain					1.377***	0.393					1.416***	0.258					1.448***	0.270
Q12t_1	-0.406	0.599	0.938***	0.273	0.635**	0.268	-0.103	0.341	0.681***	0.240	0.752***	0.181	0.471	0.340	0.733***	0.226	0.802***	0.178
Prodin_2005	0.068	0.520	-0.242	0.349	-0.254	0.251	-0.388	0.362	0.392	0.325	-0.111	0.248	0.050	0.356	0.278	0.312	-0.098	0.250
Procin_2005	0.941	0.590	0.909**	0.397	0.475	0.303	-0.793**	0.401	0.422	0.341	0.488*	0.266	0.190	0.369	0.621*	0.335	0.523*	0.268
Q16_3t_1	0.656	0.855	-0.135	0.344	-0.210	0.278	-0.175	0.318	0.321	0.302	0.033	0.233	-0.001	0.343	-0.140	0.310	0.063	0.222
Q16_4t_1	-0.154	0.562	-0.468	0.342	0.205	0.277	-0.249	0.365	-0.733**	0.336	-0.068	0.244	-0.490	0.362	-0.415	0.289	-0.133	0.221
Q5_export	-0.003	0.006	0.002	0.004	0.005	0.004	-0.007	0.005	0.002	0.004	0.005*	0.003	0.000	0.005	-0.000	0.003	0.005	0.003
Q31_3t_5					0.780**	0.307												
Q31_7t_5					-0.558**	0.280												
Q31_17t_5					0.631*	0.357												
Q31_18t_5					-0.477	0.366												
Log likelihood	-231.72616						-269.99494						-282.4885					
No of obs.	237						243						249					
rho1	-0..694 (1.832)						-0.197 (0.474)						-0.046 (0.376)					
rho0	0.754 (0.305)						0.829 (0.203)						0.957 (0.059)					
Wald test	p = 0.1252						p = 0.1402						p = 0.0305					

Variable in the dataset	Organisational innovation - New business practices for organising procedures						Organisational innovation - New methods of organising work responsibilities						Organisational innovation - New methods of organising external relations					
	Participation in support programme		Non-participation in support programme		Selection decision		Participation in support programme		Non-participation in support programme		Selection decision		Participation in support programme		Non-participation in support programme		Selection decision	
	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error
Q2_2009	0.000	0.003	0.007**	0.003	-0.002	0.002	0.006**	0.003	0.003	0.003	-0.001	0.002	0.004	0.003	-0.003	0.004	-0.003	0.002
Q4t_5	-0.233	0.299	-0.322	0.284	0.362	0.243	-0.480*	0.288	-0.009	0.247	0.061	0.201	-0.098	0.300	0.216	0.306	0.190	0.238
Q3t_1	-0.692	0.950	-1.270**	0.607	-0.757	0.634	7.498***	0.456	-0.031	0.533	-0.101	0.466	-0.354	0.794	-0.869	0.707	-0.209	0.588
Q3t_2	-0.405	0.525	1.111*	0.606	-0.353	0.375	0.465	0.459	0.262	0.480	0.066	0.378	-0.326	0.499	0.019	0.642	-0.555	0.389
Q3t_3	-0.414	0.486	0.040	0.434	-0.311	0.407	0.089	0.444	0.351	0.378	-0.122	0.301	-0.018	0.464	-0.284	0.477	-0.522	0.397
Q3t_4	-0.064	0.346	-0.252	0.362	0.328	0.278	0.496	0.346	-0.056	0.310	0.222	0.241	0.200	0.354	-0.260	0.380	0.128	0.294
Q3t_5	0.370	0.545	-0.138	0.453	-0.059	0.406	0.292	0.441	-0.014	0.368	-0.310	0.338	-0.204	0.569	0.221	0.425	-0.034	0.407
Q3t_6	-0.017	0.446	0.700*	0.420	-0.817**	0.346	-0.390	0.371	-0.382	0.357	-0.567*	0.313	-0.157	0.404	-0.688	0.423	-1.263***	0.408
Germany							-0.880**	0.387	0.325	0.354	0.467	0.302						
France																	0.945**	0.474
Spain	-0.386	0.378	-1.356***	0.446	1.635***	0.304					1.287***	0.282					2.004***	0.380
Q12t_1	-0.099	0.275	0.891***	0.312	0.774***	0.208	-0.072	0.267	1.079***	0.229	0.759***	0.180	0.182	0.272	-0.176	0.302	0.698***	0.209
Prodin_2005	-0.152	0.336	-0.024	0.374	-0.164	0.289	0.050	0.291	0.193	0.324	-0.079	0.239	-0.249	0.342	0.324	0.351	-0.480	0.316
Procin_2005	0.321	0.344	0.815*	0.423	0.125	0.311	0.209	0.348	0.886***	0.337	0.570**	0.252	0.024	0.354	0.175	0.402	0.274	0.323
Q16_3t_1	-0.266	0.290	-0.084	0.380	-0.224	0.267	-0.179	0.272	0.142	0.292	0.159	0.217	-0.362	0.317	0.228	0.328	-0.373	0.275
Q16_4t_1	0.236	0.319	-0.631	0.418	0.197	0.274	0.014	0.309	-0.409	0.302	-0.085	0.227	-0.252	0.333	-0.796*	0.425	0.416	0.293
Q5_export	0.012***	0.004	0.002	0.005	0.006*	0.003	-0.006	0.004	0.003	0.004	0.005*	0.003	0.002	0.004	0.005	0.005	0.007*	0.004
Q18_yes					1.800***	0.234											1.659***	0.249
Q31_3t_5					0.859***	0.228											0.743***	0.252
Q31_7t_5					-0.529**	0.245											-0.911***	0.269
Q31_12t_5																	0.880***	0.282
Log likelihood	-238.63978						-293.23249						-231.50041					
No of obs.	245						256						233					
rho1	-0.682 (0.177)						-0.768 (0.284)						-0.584 (0.208)					
rho0	-0.211 (0.332)						0.802 (0.195)						0.034 (0.434)					
Wald test	p = 0.0293						p = 0.0293						p = 0.0950					

Variable in the dataset	Process innovation - combined						Organisational 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.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error
Q2_2009	0.007	0.005	0.006**	0.003	-0.001	0.002	0.010*	0.005	0.008*	0.004	-0.001	0.002
Q4t_5	-0.115	0.419	-0.519**	0.261	0.095	0.202	-0.612**	0.305	0.050	0.291	-0.031	0.213
Q3t_1	7.257***	0.847	-0.665	0.511	-0.182	0.478	7.319***	0.444	-0.996	0.658	-0.178	0.443
Q3t_2	0.570	0.694	0.443	0.516	0.034	0.372	0.168	0.505	1.055	0.685	-0.156	0.417
Q3t_3	-0.079	0.553	0.392	0.417	-0.108	0.296	0.583	0.428	0.487	0.455	-0.378	0.329
Q3t_4	0.373	0.478	0.237	0.344	0.360	0.237	0.239	0.358	0.232	0.375	0.384	0.257
Q3t_5	0.462	0.629	0.060	0.410	-0.008	0.320	0.628	0.560	0.420	0.418	-0.063	0.350
Q3t_6	7.404***	0.742	0.473	0.358	-0.580*	0.328	-0.075	0.365	-0.075	0.356	-0.785**	0.366
France											0.230	0.337
Spain					1.437***	0.267					1.597***	0.344
Netherlands							0.245	0.414	-0.189	0.361	0.461	0.324
Italy							0.471	0.379	-0.047	0.297	0.195	0.311
Portugal							0.551	0.557	6.964***	0.476	-0.117	0.400
Q12t_1	-0.344	0.423	0.974***	0.250	0.688***	0.173	0.062	0.244	0.769***	0.281	0.695***	0.188
Prodin_2005	-0.159	0.439	-0.066	0.370	-0.127	0.241						
Procin_2005	0.945*	0.525	0.511	0.380	0.400	0.253						
Q16_3t_1	0.727	0.551	-0.190	0.308	0.075	0.219	-0.097	0.264	-0.098	0.319	0.000	1.000
Q16_4t_1	-0.331	0.429	-0.334	0.286	-0.093	0.227	-0.229	0.265	-0.816**	0.343	-0.022	0.217
Q5_export	-0.008	0.005	-0.002	0.004	0.005*	0.003	0.002	0.004	0.004	0.005	0.003	0.003
Q31_3t_5											0.548**	0.232
Q31_10t_5											0.170	0.249
Q31_17t_5											0.455	0.311
Q31_18t_5											-0.343	0.275
Log likelihood	-248.48591						-257.07733					
No of obs.	261						243					
rho1	-0.406 (0.588)						-0.999 (0.005)					
rho0	0.9999 (0.002)						0.655 (0.344)					
Wald test	p = 0.0183						p = 0.0783					

Variable in the dataset	**Changes in design and packaging**						**New media or techniques for product promotion**						**New methods for sales channels**					
	Participation in support programme		Non-participation in support programme		Selection decision		Participation in support programme		Non-participation in support programme		Selection decision		Participation in support programme		Non-participation in support programme		Selection decision	
	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error
Q2_2009	-0.001	0.003	-0.001	0.003	-0.000	0.002	0.004*	0.002	-0.004	0.004	-0.001	0.002	0.002	0.003	-0.001	0.005	-0.002	0.003
Q4t_5	0.374	0.354	-0.189	0.260	0.097	0.226	-0.708**	0.302	-0.461	0.339	-0.024	0.222	-1.176**	0.495	0.163	0.311	0.479*	0.267
Q3t_1	0.437	0.827	0.295	0.602	-0.494	0.491	-0.179	0.522	-0.963	0.774	0.128	0.454	-6.119***	0.660	-0.093	0.682	-0.053	0.706
Q3t_2	1.032*	0.615	1.565*	0.805	0.062	0.438	-0.003	0.482	0.917	0.631	0.081	0.396	1.223*	0.650	0.620	0.680	-0.723	0.444
Q3t_3	1.114**	0.557	0.948**	0.373	-0.179	0.366	0.823*	0.486	0.826*	0.483	-0.139	0.346	2.444***	0.761	0.493	0.497	-0.627	0.434
Q3t_4	0.300	0.404	0.200	0.317	0156	0.272	0.597	0.426	-0.415	0.449	0.137	0.258	0.262	0.419	-0.448	0.490	0.140	0.303
Q3t_5	-0.508	0.665	0.192	0.423	-0.289	0.377	-0.214	0.506	-0.554	0.500	-0.131	0.386	0.336	0.570	-0.112	0.540	-0.323	0.414
Q3t_6	0.964**	0.480	0.584	0.385	-0.600*	0.357	0.601	0.451	-0.900*	0.531	-0.670*	0.353	0.178	0.472	0.441	0.441	-1.081***	0.390
Germany	-0.809*	0.460	0.047	0.577	0.782**	0.354	-0.706*	0.403	-7.607**	3.219	0.724**	0.334						
France													-0.653	0.616	-0.407	0.534	0.443	0.461
Netherlands							-0.307	0.459	-0.808*	0.458	0.204	0.317						
Portugal													1.147*	0.626	-0.247	0.598		
Italy							-1.152***	0.432	0.371	0.360	0.300	0.269						
Spain					1.312***	0.369	-0.908**	0.442	-0.831	1.304	1.321***	0.332					1.811***	0.364
Q12t_1	0.769**	0.386	0.817***	0.243	0.827***	0.189	-0.441	0.287	0.711	0.445	0.770***	0.191	0.428	0.306	0.872***	0.330	0.862***	0.219
Prodin_2005	-0.008	0.373	0.392	0.380	-0.157	0.259	0.155	0.353	0.341	0.428	-0.217	0.247	-0.079	0.404	0.403	0.411	-0.542**	0.273
Procin_2005	0.109	0.407	0.604	0.338	0.412	0.276	-0.361	0.344	0.551	0.487	0.416	0.273	-0.226	0.405	0.482	0.531	0.289	0.307
Q16_3t_1	-0.020	0.364	-0.463	0.355	0.083	0.245	-0.589*	0.307	-0.408	0.403	-0.193	0.249	-1.216***	0.416	-0.399	0.419	-0.256	0.290
Q16_4t_1	-0.164	0.387	0.361	0.461	-0.141	0.272	0.406	0.364	-0.556	0.430	0.120	0.254	0.654	0.441	-0.279	0.435	0.221	0.304
Q5_export	-0.003	0.005	0.006	0.004	0.004	0.004	0.001	0.005	0.008	0.005	0.006*	0.003	-0.006	0.005	0.013**	0.005	0.006	0.004
Q18_yes																	1.874***	0.275
Q31_3t_5											0.457**	0.208					0.823***	0.279
Q31_6t_5					0.466**	0.198					0.432**	0.208						
Q31_7t_5											-0.269	0.230					-1.018***	0.289
Q31_10t_5											0.317	0.253						
Q31_17t_5					-0.560	0.372					0.086	0.292					0.873***	0.313
Q31_18t_5					-0.458	0.295												
Log likelihood	-255.91108						-239.63116						-198.79866					
No of obs.	235						235						237					
rho1	0.168 (0.871)						-0.891 (0.166)						-0.384 (0.313)					

rho0	0.872 (0.368)					0.392 (0.941)					0.645 (0.533)				
Wald test	p = 0.1133					p = 0.0702					p = 0.2368				

Variable in the dataset	**Marketing innovation - New methods of pricing**						**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.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error
Q2_2009	0.003	0.003	-0.000	0.003	0.001	0.002	0.001	0.003	-0.002	0.003	-0.003	0.003
Q4t_5	-0.033	0.318	-0.138	0.311	-0.162	0.213	-0.704**	0.329	-0.269	0.290	0.484*	0.261
Q3t_1	0.646	0.856	-6.109***	0.274	-0.071	0.430	0.243	0.776	-0.201	0.693	0.194	0.686
Q3t_2	0.610	0.592	1.129	0.713	-0.211	0.417	6.740 ***	1.825	7.238***	0.419	-0.503	0.410
Q3t_3	0.111	0.490	-0.098	0.423	-0.175	0.310	7.721***	2.049	0.899*	0.465	-0.342	0.395
Q3t_4	0.058	0.355	-0.276	0.387	0.275	0.247	0.717*	0.367	0.132	0.361	0.224	0.298
Q3t_5	-0.087	0.630	-0.225	0.421	-0.177	0.343	-0.096	0.489	-0.015	0.432	-0.246	0.386
Q3t_6	0.213	0.391	-0.113	0.372	-0.445	0.344	-0.221	0.513	0.725	0.461	-1.054***	0.369
Germany					0.608**	0.294						
France	-6.516***	1.637	0.081	0.398	0.282	0.329						
Spain					1.236***	0.349	0.954*	0.520	-0.737	0.473	1.708***	0.311
Q12t_1	0.273	0.307	0.040	0.317	0.683	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							-0.783 **	0.343	-0.844**	0.355	-0.081	0.270
Q16_4t_1							0.247	0.396	0.051	0.367	0.067	0.277
Q5_export	-0.002	0.004	-0.002	0.005	0.003	0.003	-0.001	0.005	0.004	0.006	0.004	0.004
Q18_yes											1.972***	0.248
Q31_3t_5					0.612***	0.191						
Q31_6t_5												
Q31_7t_5											-0.597**	0.236
Q31_10t_5												
Q31_17t_5					0.448	0.280					0.898***	0.315
Log likelihood	-271.47548						-219.12568					
No of obs.	253						241					
rho1	-0.611 (0.290)						0.809 (0.187)					
rho0	-0.755 (0.524)						-0.071 (0.353)					
Wald test	p= 0.0919						p = 0.0651					

Variable in the dataset	**Innovative sales > 5 %**						**Innovative sales > 10 %**					
	Participation in support programme		Non-participation in support programme		Selection decision		Participation in support programme		Non-participation in support programme		Selection decision	
	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stander ror
Q2_2009	0.004	0.006	0.005*	0.003	-0.000	0.002	-0.002	0.003	0.004	0.003	-0.002	0.003
Q4t_5	-1.656***	0.506	-0.817***	0.303	0.002	0.212	-0.375	0.333	-0.911**	0.382	0.368	0.263
Q3t_1	6.147***	1.061	0.425	0.672	-0.201	0.495	-0.161	0.763	1.001	0.855	0.271	0.694
Q3t_2	7.123***	1.244	-0.547	0.621	-0.307	0.435	-0.481	0.504	-0.201	0.623	-0.482	0.440
Q3t_3	-0.299	0.617	-0.099	0.500	-0.280	0.317	0.102	0.464	-0.636	0.432	-0.390	0.400
Q3t_4	0.995	0.615	-0.128	0..369	0.448*	0.248	-0.465	0.431	-0.534	0.428	0.287	0.322
Q3t_5	-0.336	1.193	0.025	0.461	0.027	0.373	0.531	0.652	0.017	0.443	0.072	0.409
Q3t_6	-0.518	0.586	-0.787*	0.462	-0.698**	0.335	-0.635	0.563	-0.763	0.555	-0.994***	0.372
Germany	-1.614**	0.647	0.416	0.412	0.531*	0.313						
France	6.553***	2.041	0.349	0.481	0.766**	0.329						
Spain					1.583***	0.292	-1.488***	0.389	-2.144***	0.716	1.762***	0.333
Q12t_1	0.640	0.640	1.192***	0.276	0.660***	0.179	0.281	0.355	0.903***	0.335	0.781***	0.206
Prodin_2005	0.597	0.792	0.701*	0.399	-0.209	0.245	1.365***	0.492	0.658*	0.387	-0.449	0.277
Procin_2005	7.732***	1.397	1.028**	0.424	0.516*	0.287	-0.437	0.485	2.181***	0.499	0.137	0.325
Q16_3t_1	-0.668	0.551	-0.619*	0.317	-0.189	0.227	0.348	0.362	-0.159	0.350	-0.126	0.284
Q16_4t_1	0.123	0.520	-0.228	0.312	0.270	0.236	-0.210	0.404	-0.285	0.379	0.247	0.298
Q5_export	-0.002	0.011	0.005	0.004	0.007**	0.003	0.002	0.005	0.004	0.006	0.004	0.004
Q18_yes											1.871***	0.331
Q31_3t_5					0.707***	0.220					0.720***	0.230
Q31_7t_5					-0.436	0.268					-0.713**	0.301
Q31_17t_5											0.921**	0.427
Q31_18t_5												
Log likelihood	-223.26741						-209.01697					
No of obs.	250						241					
rho1	-0.488 (1.480)						-0.785 (0.479)					
rho0	0.805 (0.157)						0.150 (0.591)					
Wald test	p = 0.0902						p = 0.0613					

Variable in the dataset	Innovative sales > 15 %						Innovative sales > 25 %					
	Participation in support programme		Non-participation in support programme		Selection decision		Participation in support programme		Non-participation in support programme		Selection decision	
	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error	Coeff.	Stand error
Q2_2009	-0.004	0.003	-0.000	0.003	-0.000	0.002	-0.002	0.003	-0.003	0.003	-0.002	0.002
Q4t_5	-0.070	0.306	-0.441	0.272	-0.026	0.223	-0.020	0.349	-0.173	0.298	0.272	0.252
Q3t_1	0.128	0.698	0.305	0.630	-0.023	0.501	-0.322	0.859	-0.269	0.731	0.287	0.688
Q3t_2	0.153	0.497	-0.681	0.640	-0.111	0.436	0.404	0.618	-0.779	0.736	-0.536	0.470
Q3t_3	-0.162	0.432	-0.736*	0.396	-0.232	0.313	0.095	0.493	0.137	0.450	-0.442	0.417
Q3t_4	0.175	0.357	-0.451	0.431	0.383	0.254	-0.457	0.386	-0.549	0.371	0.240	0.293
Q3t_5	0.683	0.576	-0.739*	0.445	-0.101	0.347	1.253**	0.513	-0.176	0.448	0.166	0.407
Q3t_6	-0.585	0.486	-0.963**	0.465	-0.623	0.308	0.272	0.520	-0.053	0.539	-1.034***	0.392
Germany	-0.194	0.417	-0.566	0.644	0.510	0.330	-0.512	0.451	-0.572	0.517	0.370	0.306
Spain					1.393***	0.254	-1.437***	0.463	-7.652***	0.608	1.851***	0.374
Q12t_1	0.595**	0.244	0.779***	0.288	0.681***	0.180	-0.109	0.296	0.092	0.316	0.715***	0.205
Prodin_2005	0.711*	0.432	0.085	0.314	-0.064	0.241	0.939**	0.385	0.421	0.366	-0.434	0.268
Procin_2005	0.128	0.381	1.465***	0.373	0.417	0.255	-0.175	0.390	0.501	0.422	0.156	0.290
Q16_3t_1	-0.064	0.297	-0.083	0.307	-0.101	0.231	-0.173	0.323	-0.287	0.352	-0.144	0.278
Q16_4t_1	-0.071	0.312	-0.166	0.347	0.181	0.239	0.042	0.328	-0.549	0.437	0.289	0.294
Q5_export	0.003	0.004	0.009**	0.004	0.006*	0.003	-0.002	0.005	0.012**	0.005	0.006	0.004
Q18_yes											1.806***	0.274
Q31_3t_5					0.385	0.305					0.687***	0.229
Q31_5t_5					0.260	0.288						
Q31_7t_5					-0.406	0.274					-0.617*	0.318
Q31_17t_5											0.813**	0.378
Log likelihood	-275.66835						-206.64658					
No of obs.	247						241					
rho1	0.720 (0.414)						-0.521 (0.413)					
rho0	0.684 (0.482)						-0.756 (0.357)					
Wald test	p= 0.1019						p = 0.0591					

Note: *, **, * Statistically significant at, respectively, the ten, five and one per cent levels.**