# Does Innovation Cause Exports?

## Evidence from Exogenous Innovation Impulses and Obstacles Using German Micro Data

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**Abstract**

Trade and growth theories predict a mutual causation of innovation and exports. We test empirically whether innovation causes exports using a uniquely rich German micro dataset. Our instrumental-variable strategy identifies variation in innovative activity that is caused by specific impulses and obstacles reported by the firms, which can reasonably be viewed as exogenous to firms' export performance. We find that innovation attributable to this variation leads to an increase of about 10 percentage points in the export share of German manufacturing firms. The evidence is robust to several alternative specifications and similar for product and process innovations.



**JEL Classification:** F1, O3, L1

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## 1. Introduction

This paper presents an empirical test of the prediction of product-cycle models of international trade à la Vernon (1966) and Krugman (1979) that innovation is the driving force for industrialized countries' exports – taking into account the possibility that these exports may themselves be a cause of the innovative activities, as predicted by global-economy models of endogenous innovation and growth à la Grossman and Helpman (1991b) and Young (1991).

The potential endogeneity of innovation to trade raises a severe problem for empirical tests of trade theories, because it gives a particular reason for the general truism that correlation need not mean causation. Therefore, to test whether innovations cause exports in industrialized countries, we need to identify variation in innovations that is exogenous to export performance. Our identification strategy takes advantage of a unique micro dataset of an innovation survey of German manufacturing firms. In this survey, the firms do not only report whether they have pursued product or process innovations in the preceding year, their export share and relevant control variables, but also whether specific impulses furthered their innovation and whether specific obstacles hindered their innovation. By using certain innovation impulses and obstacles that are credibly exogenous to the firms' export performance as instruments for the actual innovative activity, we can identify variation in innovations that is exogenous to exports. We argue that this instrumental-variable (IV) strategy yields estimates of the causal effect of innovation on exports in an industrialized country. As examples of our instruments, we use information on innovation impulses such as suggestions from the firms' production and resource management and on innovation obstacles such as the lack of equity capital. While this identification strategy allows us to test whether innovations cause exports, as predicted by the trade models, it does not allow for a separate estimation of the reverse effect of exports on innovations, as predicted by the endogenous growth models.

The empirical literature on exports has become increasingly aware of the need for disentangling the direction of causality between exports and measures of firm performance. Thus, Bernard and Jensen (1999) show that for some performance measures (particularly employment growth), it is both the case that superior performance precedes exporting and exporting precedes superior performance – i.e., the (chronological) causality runs both ways. Therefore, the existing evidence on (proxies for) innovation and exports (e.g., Gruber et al. 1967; Fagerberg 1988; Greenhalgh et al. 1994; Bleaney and Wakelin 2002) cannot answer the question whether innovations cause exports, because the observed correlation might have been caused by the reverse causation. Unfortunately, despite the fact that Bernard and Jensen (1999) motivate their study by potential links between innovation and exports, they do not have innovation data that would allow them to disentangle the causation between exports and innovations, but only between exports and several other performance measures. Our data and specification allow us to directly test whether innovations cause exports.

Our identification strategy for causal effects is also notably different from the one employed by Bernard and Jensen (1999). In essence, their causality test follows the Granger-causality idea, estimating whether one variable precedes another variable chronologically. However, in a world of persistent rapid technological changes, contemporaneous causation of exports by innovations may well be the most relevant time span when looking at annual data. We propose an alternative identification strategy for the causal effect of innovations on exports based on contemporaneous cross-sectional data, using variation in innovations that is credibly exogenous to exports. We argue that certain impulses and obstacles to innovation provide a quasi-experiment. They treat only part of all firms, causing them to or preventing them from innovating in a way that is exogenous to the error term of the export regression. That is, the division into innovation "treatment group" and non-innovation "control group" is random with regard to exports. In the absence of an actual randomized controlled experiment, we argue that using the impulses and obstacles as instruments for actual innovations establishes quasi-experimental variation that allows an econometric estimation of the causal effect of innovations on exports.

The paper is structured as follows. Section 2 briefly places our contribution into the existing literature on the subject. Section 3 describes the database, specific features of which are exploited in our econometric identification strategy described in Section 4. Section 5 presents our results, and Section 6 concludes.

## 2. The Literature on Innovation and Exports

### *2.1 Theory*

There are two broad strands of theoretical literature predicting a relationship between innovation and exports. On the one hand, there are international trade models stressing product-cycle features in the production of goods over time. These trade models tend to take innovation as exogenous and predict that innovation influences exports. Models featuring such a product cycle in North-South trade include Vernon (1966), Krugman (1979), and

Dollar (1986), among others. The basic prediction of all these models is that developed countries export innovative goods, which are later imitated by developing countries as these goods become mature, so that finally developing countries will export these goods to the developed countries. For developed countries to keep up their exports (and incomes), they must continually innovate. The more they innovate, the larger are their exports. This is the prediction that we want to test empirically in this paper.

On the other hand, there are endogenous growth models that recognize open-economy effects. These growth models endogenize the rate of innovation and predict dynamic effects of international trade on innovative activity. Models featuring such effects include Grossman and Helpman (1989; 1990; 1991a; 1991b, chs. 11 and 12), Segerstrom et al. (1990), Young (1991), and Aghion and Howitt (1998, ch. 11).[1]

Given the predictions of the product-cycle trade models and the global-economy growth models, we would expect a mutual causation of innovation and exports. Thus, the open-economy growth models pose an endogeneity problem for empirical tests of the prediction of trade models that trade may be influenced by innovation.

### *2.2 Empirical Evidence*

There is a large empirical literature testing the effect of innovative activity on export performance. Most studies in this literature tend not to account explicitly for the possible endogeneity of innovation with respect to exports and interpret a conditional correlation between exports and proxies for innovation as evidence in support of the predictions of the product-cycle models of trade. Initial contributions compared the export performance for US industries to innovation proxies such as research and development (R&D) expenditure and personnel (cf. Gruber et al. 1967; Keesing 1966, 1967). Subsequently, several studies looked at case studies of firms' R&D and export performance (e.g., Hirsch and Bijaoui 1985) and at cross-country evidence linking trade data with data on R&D expenditure and patents (e.g., Soete 1981; Fagerberg 1988). Several later contributions used extensive industry-level time-series data relating export performance to innovation proxies such as measures of R&D, innovation count data, and patent counts, particularly for the United Kingdom (e.g., Greenhalgh 1990; Buxton et al. 1991; Greenhalgh et al. 1994). More recently, more extensive firm-level data have become available, enabling analyses of the relationship between export

[1] Mansfield et al. (1979) produced first tentative evidence on causality running from trade to R&D activities.

performance and innovation proxies at the micro level (e.g., Wakelin 1998; Sterlacchini 1999; Bleaney and Wakelin 2002). In light of the theoretical arguments discussed above, we should interpret the evidence produced by all these studies as descriptive rather than causal.

Most of the studies in this literature are probably quite aware of the possible endogeneity of innovative activity with respect to exports. For example, Keesing (1967) already hinted at a possible "feedback loop" of causality running from trade success to R&D performance. There are some studies that take this possible endogeneity of firm performance to export performance explicitly into account. Specifically, Clerides et al. (1998) present Granger-causality tests on the relationship between exports and firm productivity. Thereby, they can distinguish whether higher firm productivity leads to subsequent exporting from the reverse sequence. Similarly, Bernard and Wagner (1997) and Bernard and Jensen (1999) analyze the chronological sequence of firms' export performance and their performance in other respects, such as productivity, size, and capital intensity. While these studies perform such time-sequence analyses for several measures of firm performance, they lack data on innovation to perform a similar analysis for the export-innovation link. Furthermore, the identification of causality in the Granger sense comes from the chronological order observations. While the first well-known general problem with the concept of Granger-causality – forward-looking adjustments in a world of expectations – may not be severe in an analysis of innovations and exports, the second problem – contemporaneous mutual causation – may well be relevant. Since technological adoption and advancement in many industries are so rapid that this year's innovation has been imitated in other parts of the world or is even obsolete in the following year, innovative activity may affect this year's export performance, but not next year's.

Also in that part of the export literature that directly relates to innovation, some attempts have been made to account for the possible endogeneity of innovation with respect to exports. These studies use simultaneous equation systems to disentangle the determination of exports in an export equation from the determination of innovation in an innovation equation. An early contribution in this direction is Hughes (1986), who uses data on a cross-section of 46 UK manufacturing industries. More recently, Smith et al. (2002) use cross-sectional Danish firm data. However, similar to the studies previously mentioned, both studies are subject to limitations with respect to measurement of innovative activity as well as identification. While they do make use of proxies for innovation, these are measures of R&D activity, which have often been argued to proxy only weakly for actual innovative activity (see Section 3.2 below). With respect to identification, both studies have to (implicitly) make assumptions on exclusion restrictions which enable an identification of the export equation from the innovation equation. To this extent, Hughes (1986) assumes, for example, that the fractions of skilled manual workers and of professional and technical staff, the capital-labor ratio, and a scale indicator affect exports but not R&D, and that previous output growth and the sales share of foreign-owned firms affect R&D but not exports. Likewise, Smith et al. (2002) make the assumption that wage share, average salary, and financial solvency affect exports but not R&D, while a food industry dummy, concentration, and minimum efficiency scale affect R&D but not exports, and they actually do not seem to provide for a direct effect of exports on innovation. Both sets of assumptions seem rather hard to defend, but without them, identification of the models would break down.

In light of the state of the theoretical and empirical literature, our alternative strategy to identify exogenous variation in innovation may help to advance the literature in terms of an understanding of the causal effect of firms' innovative activity on their export performance.

## 3. Database and Descriptive Statistics

This section discusses data issues, starting with a description of the ifo Innovation Survey, followed by a discussion of the advantages and drawbacks of our innovation measure and by descriptive statistics of our data.

### *3.1 The ifo Innovation Survey*

We use data from the 2002 ifo Innovation Survey (ifo Innovationstest), a survey conducted annually among German manufacturing firms by the ifo Institute for Economic Research at the University of Munich.[2] In multi-product firms, the unit of observation is each specific product range within the firm rather than the whole firm, allowing for a more detailed assessment than usual of where in large firms innovations occur. For the remainder of the paper, we will refer to the unit of observation as a "firm". Altogether, our sample includes 981 firms.[3] In terms of employment, the firms responding to the 2002 ifo Innovation Survey represent 11.3% of German manufacturing (Penzkofer 2004).

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[2] For details on the ifo Innovation Survey, see Penzkofer (2004). Studies having used previous versions of the ifo Innovation Survey data include Flaig and Stadler (1994) and Smolny (1998; 2003).

[3] Out of the total of 1215 respondents, we dropped 227 firms which did not report their export share as well as seven firms which gave inconsistent answers to the innovation questions, leaving us with a sample of 981 firms with consistent data on innovation and exports. A look at the descriptive statistics shows that the exclusions do not introduce any significant bias regarding the export and innovation variables. The mean export share changes statistically insignificantly from 25.4% to 25.6%, and mean innovation from 44.7% to 45.4%.

The firms report whether or not they have introduced an innovation in the preceding year (2001). Innovations are defined as new or substantially improved products or processes. We use this dummy on innovative activity during the preceding year as our main measure of innovation. As a second innovation measure, firms also report their innovation expenditure as a share of total turnover.

In addition to the innovation information, the ifo Innovation Survey includes information on the share of exports in total turnover. Furthermore, the survey collects data on additional firm characteristics such as total annual turnover, region of location (at the level of the 16 German states (Bundesländer)), and industry sector (15 sectors following the 2-digit NACE industrial classification of the European Communities), among others. In addition, we match these ifo Innovation Survey data with information on the number of employees reported by the same firms in the monthly ifo Business Climate Survey (ifo Konjunkturtest).

Finally, the ifo Innovation Survey inquires about the relevance for the firms' innovative activities of 16 specific innovation impulses and 21 specific innovation obstacles. Firms were asked to assess the importance of these impulses and obstacles on a 4-point scale. In our IV estimations, we will use some of these impulse and obstacle data as instruments for whether innovations have actually been implemented. The survey implicitly assumes that all firms which did not pursue any innovative activity (whether begun, terminated, or implemented) over the preceding year did not face any innovation impulse. Thus, these firms were asked to skip the impulse questions, and the impulses were set to the lowest possible value. Since at the very least, it is evident that the innovation impulses were not important enough to induce innovative activity in these firms, this seems like a reasonable approximating assumption. With respect to the obstacles to innovation, non-innovators were first asked whether they did not innovate because they did not deem innovations necessary during the year or whether they did not innovate because there were obstacles to innovation. Only the latter non-innovating firms, together with the innovating firms, were then asked to report on the importance of the different obstacles. Thus, the survey implicitly assumes that neither impulses nor obstacles were relevant for the innovation decisions of those firms which did not innovate because they did not see any necessity for innovation. We will return to the issue of what this specific structure of the questionnaire means for our identification strategy in the discussion of our IV specification below (Section 4.4).

Given the extensive data in the ifo Innovation Survey on innovative activity, innovation impulses and obstacles, export shares, and other firm characteristics potentially relevant for export performance, we are able to retrieve all relevant data from a single source. This rules out any measurement error stemming from imperfect matching of units from different sources. (For a discussion of possible measurement errors stemming from other sources, see Sections 3.2 and 4.2 below.)

Given our database, we analyze how innovations during the preceding year affect the export share at the end of that year. We think that this represents a relevant time frame for an analysis of the impact that innovative activity has on a firm's export performance, particularly with our measure of innovation representing any kind of product or process innovation that is new or substantially improves on previous conditions. In an era of rapid technological change, the recurrence of innovations is increasingly rapid. Firms must accelerate the process of preparing exports in order to remain competitive not only with domestic competitors but also with foreign competitors. Without continuous innovative activity, standardized production is rapidly imitated in other parts of the world. Furthermore, new innovations this year may replace last year's innovations, making the previous ones rapidly obsolete. Therefore, the time frame of a firm's export performance being affected by innovative activities during the preceding year seems warranted. Such a strategy assumes that innovations show an effect on exports already at the end of the year of their implementation. While we do not want to rule out the possibility that certain innovations, particularly drastic product innovations, require a longer time before taking effect on firms' export performance, we stick to the contemporaneous time frame in this study, leaving extensions to longer time lags to be exploited by future research.

### *3.2 Advantages and Drawbacks of the Innovation Measure*

Based on firms' responses on a survey of whether they have introduced any innovation in the preceding year, our measure of innovation is a direct measure of the output of the innovation process at the firm level. The innovation measure captures both product or process innovations (which we can distinguish, cf. Section 5.5 below) that have led to new or substantially improved products or processes. We disregard innovative activities which are still in the planning phase or which have been discontinued, restricting our measure to only those innovations that are actually introduced, either as products that can already be obtained on the market or as processes applied at the factory floor. The measure includes both discontinuously occurring major technological breakthroughs and more regularly occurring innovations at less grand a scale, which form an important part of the technological process of economies. The survey covers the whole range of firm sizes from small over medium to large firms.

In comparison to other proxies for innovative activity often used in the literature, particularly R&D measures, patent measures, and literature-based innovation counts, this innovation measure has a number of advantages, as well as specific limitations. The drawbacks of the alternative measures of innovation have been discussed extensively in the literature. Kuznets (1962) already noted the severe problems that a lack of appropriate innovation measures poses to economic research on innovation.

Measures of R&D activity, such as reported R&D expenditure or fraction of employees in R&D departments, reflect the input side of the innovation process. However, there are considerable problems in the measurement of R&D. For example, Griliches (1979, p. 99) concludes that "much of the product of research and development is entirely unmeasured and much of the rest is mismeasured." Furthermore, Kleinknecht (1987) shows that existing F&E measures are considerably biased towards underestimating the innovative activities of small firms. But even with R&D properly measured, R&D may be only a poor measure for actual innovation, because there is a lot of innovation taking place outside formal R&D operations, and a considerable share of R&D activities may never lead to innovations (with differing degrees of R&D effectiveness).

Likewise, the relationship between patent counts and innovation is blurred by the facts that a lot of innovations are never patented (or even patentable) and that many patents relate to inventions never being introduced into economic application (cf. Basberg 1987; Griliches 1990; Hall et al. 2001). The latter problem, occurring for example because firms patent to prevent rivals from patenting related inventions or to prevent suits (Cohen et al. 2000), may be mitigated to an extent once patent data are weighted by citations, renewal information, or reactions by firms' market value. The former problem, however, seems to be increasingly relevant, with firms choosing to protect their innovations by secrecy and lead time advantages rather than through patenting (Cohen et al. 2000).

A third measure of innovation are literature-based innovation counts by experts (e.g., Greenhalgh 1990). These have the distinct advantage of being a direct measure of innovative output. However, such counts depend on firms' publication policies as well as experts' assessments, and they do not capture marginal innovators, which account for the majority of innovative activity. Patent and innovation count data also do not provide information on non-innovators.

Obviously, there are also noteworthy drawbacks to the firm-survey-based innovation measure employed in this study. As with any survey data, the measure derives from subjective assessments, based on discretionary decisions by the respondent. The subjective assessments will introduce measurement error to our innovation data. If they were correlated with the error term of the export equation, they would also introduce bias into our estimates. Furthermore, the mere dummy information of whether any innovation was introduced during the preceding year does not allow for a count of the number of innovations introduced, let alone for a valuation of their economic importance. Only to the extent that the economic value of the innovations is related to the magnitude of innovation expenditure can we capture such heterogeneity of innovations with our second innovation measure.

Despite these limitations, our direct measure of innovation has the clear advantages of capturing also the innovations that take place without being patented, outside firms' formal R&D operations, and not cited in the literature, while at the same time disregarding patents and R&D activities that do not lead to commercially employed innovations. Furthermore, the ifo Innovation Survey data provides a lot of further useful information at the firm level and contains comparable data for firms that did not innovate. Its broad definition of innovation, encompassing both major and minor ones, probably gives a more thorough picture of the innovative activity taking place in an economy, and validates the contemporaneous time frame used in this study. If innovations in this broad sense affect export performance differently from irregular technological breakthroughs, this would affect the permissible interpretation of results.

### *3.3 Descriptive Statistics*

Of the 981 firms in our sample, 445 or 45.4% reported having introduced an innovation (Table 1). The mean innovation expenditure among the innovators is 4.5% of their total turnover. Among the firms that did not innovate, 322 firms (32.8% of the whole sample) reported not to have innovated because they did not deem innovations necessary during the year, and 91 firms (9.3%) indicated that specific obstacles hindered them from innovating. Despite pursuing innovative activities during the year, the remaining 123 firms (12.5%) were either still in the planning phase or had discontinued the innovative activity, without having introduced the innovation in the market or on the factory floor.

Exports are measured as share of total turnover in the specific product range. In our sample, 714 or 72.8% are exporters. The mean export share among the exporters is 35.1%, or

25.6% in the total sample. Among innovators, the export share averages 32.4%, while among non-innovators, it is only 19.8%. This descriptive difference is statistically highly significant ($t$-statistic 7.6). Figure 1 shows two histograms of export shares, one for the innovating firms, the other for the non-innovating firms. It is evident that non-exporting and low export shares are much more prevalent among firms that did not innovate, while larger export shares are much more prevalent among innovating firms.

Table 1 also reports descriptive statistics on firms' turnover and number of employees. The distribution of innovative activity across states (Bundesländer), firm size and industry sectors (according to NACE classification) is reported in Tables A1 and A2 in the appendix.

## 4. The Identification Strategy

This section describes our empirical identification strategy, starting with its basic idea of using exogenous innovation impulses and obstacles as instruments for actual innovative activity in the export equation. This is followed by a discussion of the choice of instruments, interpretation issues, and specifics of the use of the ifo Innovation Survey data.

### *4.1 The Basic Idea*

Our basic model is the following export equation:

$$X_i = \beta_0 + \beta_1 I_i + \beta_2 T_i + \beta_3 E_i + R_i \beta_4 + S_i \beta_5 + \varepsilon \tag{1}$$

where $X_i$ is the export share of firm $i$, $I$ is the innovation measure (either innovator dummy or innovation expenditure), $T$ is the logarithm of total turnover, $E$ is the logarithm of the number of employees, $R$ is a vector of regional dummies, $S$ is a vector of sector dummies, and $\varepsilon$ is an error term.

Thus, given our firm-level information, we can control for firm size, regional location, and industrial sector. The regional fixed effects $R$ control for differences between the 16 German states. The sectoral fixed effects $S$ control for differences between 15 industrial sectors, based on the NACE industry classification (cf. Table A2). Since much of the previous literature has shown that both the propensity to export and the propensity to innovate have strong sector-specific components, the sectoral fixed effects are vital to evade bias from unobserved heterogeneity between sectors. For example, these may stem from sector-specific demand conditions with respect to product markets, technological possibilities, and appropriability conditions. Thus, all our results are to be interpreted as within-sector effects, that is, how the differing innovativeness of one firm from other firms in the same sector affects the firm's export performance.

Given the theoretical reasoning presented in Section 2.1, ordinary least-square (OLS) estimation of equation (1) will not yield an unbiased estimate of the causal effect of innovation on exports, because the innovation measure $I$ is likely to be correlated with the error term $\varepsilon$ of the export equation due to the effects predicted by the global-economy growth models of endogenous innovation and growth. Therefore, to test whether innovations cause exports, we need an empirical strategy that identifies variation in innovation that is exogenous to exports. To this extent, we use the information on the specific innovation impulses and obstacles reported in the ifo Innovation Survey. We argue that certain impulses that lead firms to innovate and certain obstacles that prevent firms from innovating can reasonably be viewed as being exogenous to the error term of the export equation. Therefore, these impulses and obstacles can be used as instruments for actual innovative activity in a two-stage least-squares (2SLS) estimation of equation (1). These exogenous impulses and obstacles give rise to a quasi-experimental identification that divides firms into an innovation "treatment group" and a non-innovation "control group" in a way that is random with regard to firms' export performance. This identification strategy ensures that the estimate on the innovation variable is solely affected by variation in innovative activity that is exogenous to export performance, so that the 2SLS estimate can be interpreted as the causal effect of innovation on exports.

*4.2 Choice of Instruments*

The crucial element in this identification strategy is the proper choice of instruments. The two vital features of a valid instrument are that it must be strongly related to the endogenous explanatory variable – innovation in our case – while at the same time it must be unrelated to the error term of the export equation. We show in the first-stage results reported below that all the innovation impulses and obstacles that we use as our instruments are indeed strongly related to actual innovative activity, even after controlling for firm size and the regional and sectoral fixed effects. In what follows, we will argue that our instruments are reasonably exogenous to the error term of the export equation. That is, we will argue that they do not have a direct effect on exports but just the indirect effect running through their effect on innovative activity, and that they are neither primarily driven by the reverse causation running from exports to innovation, nor by omitted variables that might influence both innovation and exports.

In order to explain our choice of instruments, it helps to start from the opposite side and argue which kind of impulses and obstacles are likely to be endogenous to export performance and thus not valid as instruments in our analysis. Starting with the impulses reported in the ifo Innovation Survey, firms report, for example, whether customers were an important source of impulses for their innovative activities. Given that it is exactly the characteristics of these customers – domestic versus foreign – which differentiate exporters from non-exporters, this kind of innovation impulse clearly cannot be viewed as being exogenous to export performance. Similarly, impulses stemming from the firm's marketing department, which is directly focused on the different kinds of customers, are unlikely to be exogenous to export performance.

However, firms also report whether important impulses for their innovative activities came from reading the technical literature (TL). Arguably, such impulses affect exporters and non-exporters alike. Especially for technical literature, it seems reasonable to assume an international distribution of knowledge. Therefore, the TL impulses should be exogenous to firms' export performance, and can thus be used as instruments in our analysis. On the downside, parts of the TL may be in a foreign language, and exporting firms may be more likely to be able to read the foreign part of the TL. However, this seems unlikely to be a dominant effect for innovative activities in German manufacturing firms, and we would argue that the innovation variation identified by the TL instrument at least is less prone to endogeneity than the total innovation variation in our sample. Still, we cannot be sure that this instrument is perfectly exogenous to export performance. In the end, we will collect several instruments for our analysis, so that we can use over-identification tests to test whether certain instruments are endogenous. As long as we accept that at least one of the instruments is exogenous to export performance, these over-identification tests will detect endogeneity for any of the other suggested instruments.

A second innovation impulse that we deem reasonably exogenous to export performance are impulses stemming from the firms' production and resource management (PRM) department. In contrast to impulses stemming from the firms' marketing department which may or may not have direct contacts to foreign markets, the PRM impulses stem from the firms' factory floor, which is not directly related to the exporting unit of the firm. All the firms in our sample are located in Germany, so that the PRM impulses should not be influenced by the fact that a firm is an exporter or not.

In a way similar to the PRM impulses, impulses stemming from firms' internal employee suggestion scheme (ESS) need not be directly related to the firms' export activities. However, we are not so sure about this instrument, because at least some of the suggestions may come from the firms' sales personnel persons, which may give rise to endogeneity to the export equation.

In terms of the obstacles that firms report in the ifo Innovation Survey as limiting their innovative activity, there are again certainly some obstacles that may be endogenous to export performance. For example, one obstacle reported by the firms is that they have problems hiring capable personnel for their sales force on the labor market. The variation in innovative activity caused by a lack of qualified sales employees may well have a direct effect on the variation in firms' export performance, so that this obstacle cannot serve as an instrument in our analysis. Similarly, another obstacle stems from customers' problems with accepting the new products or processes, which – being a specific feature of the customers – is likely not to be exogenous to whether firms export or not.

In contrast, we suggest that two innovation obstacles are reasonably exogenous to firms' export performance and can thus be used as instruments in our analysis. First, firms report whether lack of equity capital (LEC) was an obstacle in their innovation process. While a lack of borrowed capital may or may not be related to the firms' relative export performance, we would argue that the variation in innovations caused by a lack of equity capital is exogenous to export performance as measured by the share of exports in total turnover. Note that this will not necessarily be true for absolute exports, which may serve as a funding scheme for innovations. But since we measure exports as a share of total turnover, this will not affect the innovation possibilities, as a lower export share in other firms is just compensated by a bigger share of domestic revenue. Thus, the LEC obstacle can serve as an instrument for innovation in our export equation.

Second, firms report whether a low rate of return to innovation caused by the fact that the innovation expense is too high is an obstacle to their innovative efforts. We view such low returns due to excessive innovation expenses (LR) as exogenous to firms' export share, because the costs of an innovation can be considered exogenous to exports. Any given innovation should cost the same, independent of whether it is pursued by an exporting firm or by a non-exporting firm, particularly within the same industry (as we control for industry fixed effects).

We cannot be sure *ex ante* about the strict exogeneity of all our instruments. Finding plausible experiments and thus convincing instruments is always a matter of argument and persuasion. The bottom line is that, while it seems warranted to expect that the variation in innovation identified by the instruments is less prone to endogeneity than the total variation in innovation, there might be reasons to expect that some of the instruments may be weakly correlated with the error term of the export equation. However, once we accept that at least one of the suggested instruments is exogenous to export performance, we can test for the exogeneity of the other instruments by use of over-identification tests. This is the strategy that we will use below.

Descriptive statistics on the innovation impulses and obstacles which we use as instruments in our analysis are contained in Table 1. Given these impulses and obstacles which we view as being reasonably exogenous to firms' export shares, we can estimate equation (1) by 2SLS, using the exogenous impulses and obstacles as instruments for the measure of actual innovation $I$.

### *4.3 Interpretation as Local Average Treatment Effects*

In interpreting our results, it should be borne in mind that the variation in innovative activity which we identify by using our instruments is a specific one. The impulses and obstacles that we use as our instruments treat only certain firms, and therefore, the effects estimated by our IV strategy should be interpreted as Local Average Treatment Effects (LATE), particularly given our dummy innovation measure (Imbens and Angrist 1994). In this case, we identify the causal effect of innovation on exports for those firms whose innovation status is influenced by changing the impulse and obstacle treatment.

For example, the effects estimated using our impulse instruments identify the LATE for that specific subset of the innovators whose behavior was changed by the impulse "experiment." Thus, we identify the effect of innovation on exports for those firms which innovate because of the positive impact of the specific instrument and which would not have innovated without this impulse. Whether or not this effect is representative for a broader set of firms depends on whether there are heterogeneous treatment effects. If so, the LATE estimator identified in our study may differ from the average treatment effect for the whole universe of firms. Likewise, the effects estimated using our obstacle instruments identify the LATE for those firms whose innovation status was affected by the specific obstacle. That is, the effect is the relevant one for those firms which do not innovate because of the existence of the specific obstacle but which would innovate without this obstacle.

In our more extensive specification that combine the different instruments, the IV estimates identify the average treatment effect for a set of firms that innovates for a range of reasons related to different innovation impulses and obstacles. These broader specifications give rise to the possibility of a broader interpretation of the estimated effects. Furthermore, the kind of local variation identified by our instruments may be of intrinsic policy interest, particularly in the case of our obstacles instruments. If a specific policy could affect the innovative activity of firms by facilitating access to equity capital or by lowering the private expenses necessary for an innovation, the LATE identified in our specifications that use these obstacles as instruments are exactly the ones relevant for such a policy initiative.

*4.4 Peculiarities of the Survey Data*

As indicated in Section 3.1, the ifo Innovation Survey implicitly assumes that there were no innovation impulses for all firms that did not pursue any innovative activity, be it because they did not deem innovations necessary or because obstacles to innovation existed. These firms were asked to skip the impulse questions. We think that the assumption of a low impulse level for these firms is reasonable, and follow it in our estimations. That is, the impulse instruments mainly identify innovators, but not non-innovators, so that the identification by impulse instruments concentrates on variation between the innovating firms. The exception to this are the 123 firms that pursued innovative activities during the year but either were still in the planning phase or had discontinued the innovative activity without having introduced the innovation in the market or on the factory floor. These firms were asked to report the impulse questions and thus give us a broader range of identification.

Furthermore, the ifo Innovation Survey initially asked whether firms did not innovate because they deemed innovations unnecessary over the preceding year or because they felt that obstacles existed that hindered them from innovating. Only the latter non-innovating firms (together with the innovating firms) were asked to answer the obstacles questions, while the former non-innovating firms were asked to skip them. That is, the obstacles instruments also identify non-innovators, but only a specific part of them. Again, the firms that planned or discontinued innovations without implementing them also provide information on the obstacles instruments.

We do not have any priors as to whether the fact that firms deemed innovations unnecessary – that is, those firms for which we do not have obstacle information – is exogenous or endogenous to firms' export performance. If the former is true, we can use an indicator variable equal to one for firms that deemed innovation not necessary (INN) as an additional instrument in the first-stage (innovation) regression, using it as an exogenous explanatory variable of why firms did not innovate and thereby controlling for the fact that we do not have information on the other instruments for these firms. If the latter is true, the INN indicator also has to go into the second-stage (export) regression. We can test the two possibilities against each other by using an over-identification test, which shows whether there are invalid instruments in the first stage which should also be contained in the second stage. For all our specifications, the over-identification tests do not reject the exogeneity hypothesis for the INN indicator, suggesting that it can be used as an additional valid instrument.

We have complete data on exports and innovation in our sample of 981 firms, as well as complete data on employment, regional location, and industrial sector for all the firms. However, there are some missing observations in the data on firm turnover and on the innovation impulses and obstacles (cf. Table 1). We impute the mean of the relevant variable for missing values and include a dummy for each variable, equal to one if the value is missing for an observation and zero otherwise, in both stages of the 2SLS estimation. We also test for robustness of our results against dropping all observations for which we do not have data on the instruments.

Finally, the use of instruments in our IV strategy also serves to reduce possible measurement error in our innovation variable due to the subjective reporting in our survey data. The impulse and obstacle information adds further relevance to the innovation information. Using them as instruments can serve to provide consistent estimates even in the presence of measurement error in the actual innovation information.

## 5. Results

The section presents the results of the estimations of our empirical models, starting with OLS estimations, followed by IV results, robustness specifications, Tobit results, and separate estimations for product and process innovations.

### 5.1 OLS Estimates

As a baseline comparison, the first two columns of Table 2 report results for OLS regressions using our two innovation measures. Specification (1) uses the innovator dummy variable as defined in Section 3.1. Controlling for the firm size variables and the regional and sectoral dummies, firms that introduced an innovation over the preceding year have an export share at the end of that year that is statistically significantly higher by 3.3 percentage points than the export share of firms that did not introduce an innovation. Similarly, for each percentage point of higher innovation expenditure as a share in total turnover, firms' export share is a statistically significant 0.4 percentage points higher (specification (2)).

In terms of the control variables, firm size is a significant predictor of firms' export share. A one percent change in the total turnover in the specific product range is statistically significantly related to an export share that is slightly more than 3 percentage points higher. The dummy for observations with missing turnover data is not statistically significant. While our second measure of firm size, the number of employees, has a statistically significant positive coefficient in specifications which exclude the turnover measure, the turnover effect dominates the employment effect in specifications which include both, with the latter becoming statistically insignificant. By and large, there are few statistically significant differences between the German states (Bundesländer), once the other effects are controlled for. The small number of sampled firms in Berlin and Saarland show the largest export shares, while firms in the Eastern states tend to have the smallest export shares. As expected, there are significant sector-specific components in firms' export shares, with the publishing and printing sector (NACE 22) exhibiting the lowest conditional export share and the sectors producing machinery, equipment, and computers (NACE 29/30) and medical, precision, and optical instruments (NACE 33) the highest. The results for the control variables do not change substantially in the IV and Tobit models reported below.

### 5.2 IV Results

As suggested in Section 4.1, we can use information on innovation impulses and obstacles as instruments for actual innovative activity in a 2SLS specification to obtain estimates of the causal effect of innovation on exports. Results of these IV regressions, including their first stage results, are reported in Tables 3 and 4. Specification (5) uses the first innovation impulse, stemming from production and resource management (PRM), together with the dummy on firms deeming innovations not necessary (INN) as instruments for innovations.

The results show that if firms are led to innovate by PRM impulses, their export share rises by a statistically significant 8.2 percentage points. The Hausman test statistic suggests that this is statistically significantly different from the OLS result, so that the latter is indeed significantly biased, as suggested by the theoretical reasoning in Section 2.1.

In this specification, the PRM impulse is measured as a dummy, equaling 1 if a firm deemed this impulse to be not important and 0 otherwise. The *F*-test on the instruments in the first-stage regression suggests that the instruments are strongly related to actual innovation, even after controlling for firm size, region, and sector. There is obviously no weak-instruments problem here, with an *F*-test of 329.9. Furthermore, the Sargan test does not reject the over-identifying restrictions, suggesting that once we accept PRM as a valid, INN is also shown to be exogenous. The first-stage results show the expected effects that if PRM impulses are considered as not important, the probability of innovating is 44.8 percentage points lower. Likewise, conditional on the other controls, the INN dummy is related to an export share being 29.9 percentage points lower.

Specification (6) jointly uses the other two innovation impulses as instruments, namely impulses stemming from the employee suggestion scheme (ESS) and from the technical literature (TL). Results are quite similar with a slightly (albeit not statistically significantly) lower coefficient on innovation. Although not rejecting the over-identifying restrictions, the Sargan test comes much closer to do so in this specification. The same is true when either of these two impulses is entered individually. Furthermore, once they are entered jointly with the PRM impulse, the over-identification test rejects the exogeneity hypothesis (not shown). Given that the exogeneity assumption is not rejected once the PRM impulse is entered jointly with the obstacles instruments (see below), we suspect that there may be some endogeneity in the ESS and TL impulses, as already suspected above (cf. Section 4.2). Therefore, there is some doubt that the ESS and TL impulses are valid instruments, so that in what follows, we will focus on specifications restricted to the other instruments.

Specification (7) uses the two innovation obstacles, stemming from a lack of equity capital (LEC) and from low returns due to excessive innovation expenses (LR), as instruments for innovation.[4] Again, the obstacles are strong predictors in the first-stage regression (*F*-test on the instruments of 167.1), and the Sargan test is far from rejecting the over-identification restrictions. Both obstacles, measured as dummies equalling 1 for firms reporting the obstacle as being very important, are statistically significantly negatively related to innovations, as

4 The results for specifications entering the two obstacle instruments individually are very similar.

expected. The coefficient on innovation in the second-stage export equation is again statistically significant, suggesting that firms which did not innovate because they were affected by these obstacles had an export share that was 6.8 percentage points lower.

In the next specification (8), we jointly enter the PRM impulse and the LEC and LR obstacles as instruments. The point estimate on the innovation dummy in the export equation now equals 7.7. Tests for difference in the estimates of the effect of innovation on exports among the different IV specifications show that there is no statistically significant difference between any two of them (not shown). Given our LATE interpretation, this suggests that the export effect of innovations caused by the PRM impulse is similar to the one caused by the LEC and the LR obstacles. However, the Hausman test again rejects the exogeneity of the innovation dummy in the OLS export equation. With both the impulse and the obstacles instruments, the over-identification test is again far from rejecting exogeneity. Therefore, as long as we accept one of these instruments as valid, we can also accept the others as valid instruments. The adjusted $R^2$ of the first-stage regression is higher than in the specifications using the instruments separately, and the $F$-test on the instruments (182.1) again shows a strong correlation with innovation.

To summarize, we find a statistically significant causal effect of innovation on exports in all the IV specifications. Among the more reliable estimates, the size of this effect lies between 6.8 and 8.2 percentage points of additional export share due to the fact that firms are innovators. Tests are supportive of using the PRM impulse and the LEC and LR obstacles jointly as instruments for actual innovative activity.

### *5.3 Alternative IV Robustness Specifications*

In Table 4, we report results of alternative specifications conducted to check for the robustness of the results of our previous models. We stick to the encompassing specification of using PRM impulses and LEC and LR obstacles jointly as instruments. Results using only part of these instruments are very similar (not shown).

Instead of using one dummy for each of the instruments, specification (9) uses the full 4-category information that we have on each of the instruments. Firms were asked to assess whether each of the impulses and obstacles was not important (by answering "–"), slightly important ("1"), important ("2"), or very important ("3"). Furthermore, some firms just ticked the relevant box, presumably suggesting that the impulse or obstacle was very important. We take this as a separate, fifth category here. As can be seen in the first-stage results, the propensity to innovate increases steadily with the importance of the PRM impulse, and it decreases steadily with the importance of the LEC and the LR obstacles. The adjusted $R^2$ of the first-stage regression is slightly higher than in specification (8), while the $F$-statistic of the instruments is actually lower. The result on the effect of innovation on exports in the second-stage regression does not change significantly; neither do the other test statistics.

As an alternative test to ensure that our results are not affected by firms' non-response on the instruments, specification (10) drops the 202 observations for which at least one of the three instruments is missing. The results using this smaller sample are very similar to the ones obtained in specification (8), showing the robustness of our results with respect to our treatment of missing instruments.

Specifications (11) and (12) of Table 4 use our second innovation measure, innovation expenditure as a share of total turnover in the relevant product range. As some firms did not answer the expenditure question, this reduces the sample to 847 observations. Specification (11) uses the same instruments as specification (8) above. The results are very similar, although the LR obstacle is no longer statistically significant in the first-stage regression once the other two instruments are also entered. Innovation expenditure are the higher, the more important the PRM impulse is, and they are the smaller, the more important the LEC obstacle is. The $F$-test on the instruments and the adjusted $R^2$ of the first stage are substantially smaller than in specification (8), but still reassuringly large. The model shows that each additional percentage point of innovation expenditure in total turnover increases firms' export share by 1.5 additional percentage points.

The innovation measure now being a continuous rather than dummy variable, specification (12) uses the three instruments as categorical variables, ranging from 1 (not important) to 4 (very important). Neither the first-stage nor the second-stage results change significantly in this specification.

### *5.4 Tobit Models*

Our dependent variable, firms' export share, is not normally distributed, but rather limited at zero, with 27.2% of firms not exporting at all (cf. Table 1 and Figure 1). This censored data structure possibly biases the previously reported OLS and IV estimates. We therefore account for the structure of the limited dependent variable with a large number of non-exporters by estimating Tobit models. Results of standard Tobit regression are reported in specifications

(3) and (4) of Table 2. Both innovation measures are again statistically significantly related to firms' export share, with the coefficient estimates slightly larger than in the OLS case.

In order to account for the possible endogeneity of innovation with respect to export by use of our instruments in the Tobit model, we use Amemiya's (1978) General Least Squares (AGLS) estimator, which has been shown to be asymptotically more efficient than standard two-stage Tobit models (cf. Newey 1987). The ensuing IV Tobit results are reported in Table 5. All specifications use the preferred instrument specification from above, jointly applying the PRM impulse and the LEC and LR obstacles as instruments, in addition to the INN dummy.

Specification (13) presents the AGLS Tobit specification equivalent to the standard IV specification (8) above, using one dummy each for the PRM impulse and the LEC and LR obstacles as instruments for the innovator dummy. We again find a statistically significant effect of innovation on exports. The results now suggest that that being an innovator increases a firm's export share by 10.3 percentage points. The difference to the previous results suggests that the linear restriction imposed by the previous models does not seem to do justice to the data. Specification (14) again excludes observations with missing instrument data, yielding similar results.

Specification (15) uses the innovation expenditure measure and the same dummy instruments. Again, we find a statistically significant positive effect of increased innovation expenditure on firms' export share. In this specification, a 1 percentage point increase in the innovation expenditure (as a share of total turnover) leads to a 1.9 percentage point increase in the firm's export share. Specification (16) also uses innovation expenditure, but instruments it by the PRM impulse and the LEC and LR obstacles measured as categorical variables (see above). The results are very similar, with a coefficient estimate on innovation expenditure of 1.7.

### *5.5 Product versus Process Innovation*

So far, we have analyzed the effects of any kind of innovation, be it product or process innovation. However, we also have separate information on whether firms have introduced either a product or a process innovation. It has long been recognized that innovations are not necessarily homogeneous, and that in particular, there may be qualitative differences between product and process innovations (e.g., Lunn 1986). Therefore, the export effects of these two types of innovation may also differ. In our sample, 38.7 percent of all firms have introduced a product innovation over the preceding year, and 30.1 percent have introduced a process innovation, with the two not being mutually exclusive (cf. Table 1).

Results for our IV and IV Tobit export regressions using product and process innovations separately are reported in Table 6. We find statistically significant effects on firms' export share for both kinds of innovation. The separately estimated export effects of both kinds of innovation are slightly (but not statistically significantly) larger than the export effects estimated for the joint innovation measure. While the effect on exports is slightly larger for process than for product innovations, the difference between the two is not statistically significant.

The first-stage results are also very similar, with PRM impulses leading to both more product and more process innovation and LEC obstacles leading to both less product and less process innovation. In both cases, the effects of LR obstacles are less pronounced. Due to the substantial multicollinearity between both types of innovation, the coefficients on product and process innovations are jointly statistically significant, but individually statistically insignificant, in a specification where both types of innovation are entered jointly (not shown).

## 6. Conclusion

In this paper, we test whether innovations cause exports among German manufacturing firms, as product-cycle models of international trade would predict. Being aware of the possible reverse causality predicted by global-economy models of endogenous innovation and growth, our empirical strategy identifies variation in innovative activity that occurs because of specific impulses and obstacles for innovative activity which we would argue are largely exogenous to firms' export performance. Using the innovation impulses and obstacles as instruments for actual innovative activity, we find that the innovations emanating from the variation in these impulses and obstacles lead to a share of exports in firms' total turnover that is about 10 percentage points higher. Given a mean export share in our sample of roughly one quarter, this is a substantial effect. Therefore, our results support the prediction of the product-cycle models that innovation is a driving force for industrialized countries' exports.

We argue that by looking at innovation variation stemming from the PRM impulse and the LEC and LR obstacles, we identify variation in innovative activity that is exogenous to exports and can thus yield estimates of a causal effect of innovation on exports. The different tests we present suggest that OLS estimates are indeed biased by endogeneity, and they support the validity of the instruments in our setting. Therefore, it seems warranted to expect that the variation in innovation identified by the instruments is, at the very least, less prone to endogeneity than the total variation in innovation, and that our estimates are thus less affected by endogeneity than OLS results.

As a mere descriptive, unconditional difference, innovators showed an export share that was 12.6 percentage points higher than non-innovators. Given our results, most of this unconditional correlation between innovation and exports is due to a causal effect of innovation on exports. Only a relatively small fraction of the positive correlation seems to emanate from the reverse causation or any underlying effects influencing both innovative and export activity. Given our detailed controls for industry sectors, our results can be interpreted as within-sector effects. Being innovative causes firms to have substantially larger export shares than non-innovative firms in the same sector.

Our identification strategy can be viewed as an alternative strategy to the one based on Granger-causality ideas, as employed by Bernard and Wagner (1997), Clerides et al. (1998), and Bernard and Jensen (1999). Actually, our results are much in line with their findings that better firm performance mainly tends to precede exporting, rather than the other way round. Our results suggest that this temporal pattern may be due to the causal effect of innovative activity on exports. Likewise, our results constitute a strong micro foundation for the stylized fact that growing world trade in recent years is largely associated with increased technology-intensive exports from industrialized to relatively lagging countries (Das 2002). Given that this pattern in itself may lead to a diffusion of the innovative technology embodied in the exported products, our results are supportive of the suggestion of the product-cycle trade models (particularly Krugman 1979; Dollar 1986) that industrialized countries may have to continually innovate if they want to remain competitive on global markets and maintain their living standards.

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**Figure 1: Histogram of Export Shares among Innovating and Non-Innovating Firms**

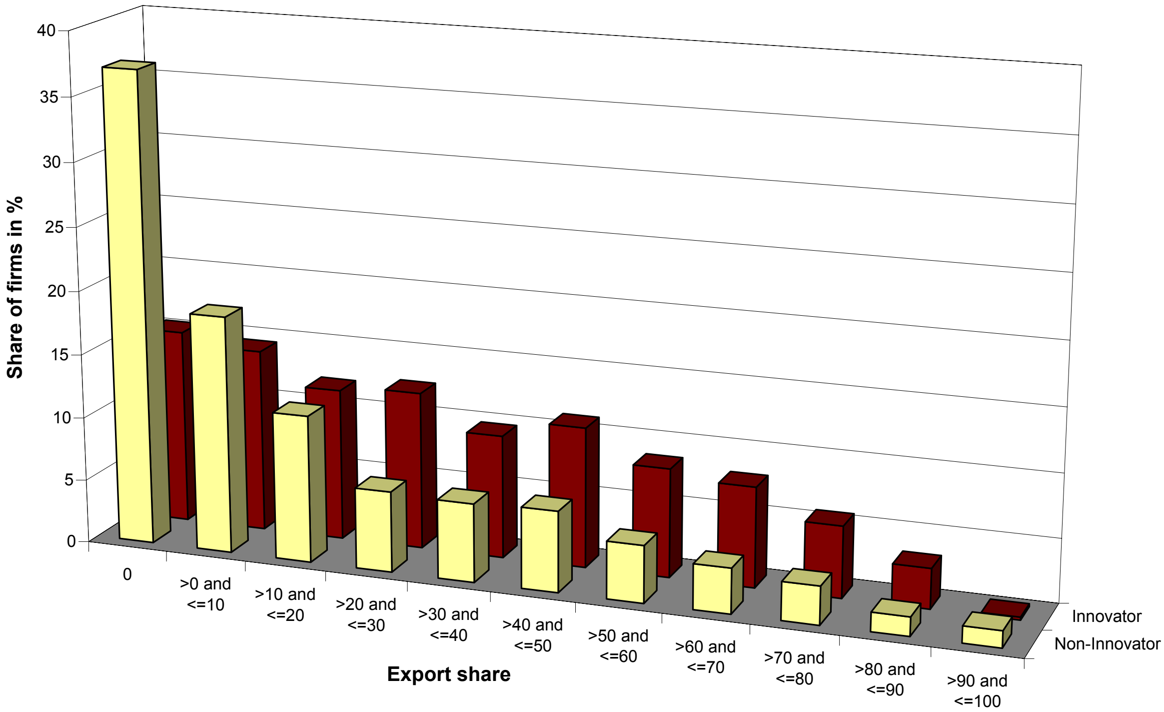

**Table 1: Descriptive Statistics**

| | N | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Innovator (dummy) | 981 | 0.454 | | 0 | 1 |
| Innovation expenditure (in % of total turnover) | 847 | 2.30 | 4.48 | 0 | 57.0 |
| - Among innovators | 344 | 4.55 | 4.92 | 0.1 | 44.7 |
| Product innovator (dummy) | 981 | 0.387 | | 0 | 1 |
| Process innovator (dummy) | 981 | 0.301 | | 0 | 1 |
| Exports (in percent of total turnover) | 981 | 25.6 | 26.6 | 0 | 100 |
| - Among exporting firms | 714 | 35.1 | 25.3 | 0.01 | 100 |
| - Among innovators | 445 | 32.4 | 26.2 | 0 | 97.5 |
| - Among non-innovators | 536 | 19.8 | 25.6 | 0 | 100 |
| Turnover (in million Euro) | 922 | 174 | 1,853 | 0.015 | 4,700 |
| Number of employees | 981 | 529 | 3,834 | 1 | 99,999 |
| PRM not important | 889 | 0.547 | | 0 | 1 |
| ESS not important | 881 | 0.680 | | 0 | 1 |
| TL not important | 855 | 0.725 | | 0 | 1 |
| INN | 981 | 0.328 | | 0 | 1 |
| LEC very important (if INN=0) | 531 | 0.168 | | 0 | 1 |
| LR very important (if INN=0) | 507 | 0.138 | | 0 | 1 |
| PRM (categorical) | 889 | 1.823 | 1.024 | 1 | 4 |
| ESS (categorical) | 881 | 1.454 | 0.746 | 1 | 4 |
| TL (categorical) | 855 | 1.380 | 0.691 | 1 | 4 |
| LEC (categorical) (if INN=0) | 531 | 2.228 | 1.172 | 1 | 4 |
| LR (categorical) (if INN=0) | 507 | 2.375 | 1.082 | 1 | 4 |

For explanation of abbreviations, see text (Section 4.2). – The categorical variables are scaled as 1= not important, 2 = slightly important, 3 = important, 4 = very important.

**Table 2: OLS and Tobit Regressions**

Dependent variable: Export share

| | (1) OLS | | (2) OLS | | (3) Tobit | | (4) Tobit | |
|---|---|---|---|---|---|---|---|---|
| Innovator | 3.293** | *(1.482)* | | | 4.870** | *(1.892)* | | |
| Innovation expenditure | | | 0.401** | *(0.172)* | | | 0.445* | *(0.230)* |
| log(turnover) | 3.223*** | *(0.819)* | 3.311*** | *(0.898)* | 4.358*** | *(1.075)* | 4.615*** | *(1.197)* |
| Turnover missing | -0.567 | *(2.897)* | -1.980 | *(3.362)* | -3.019 | *(3.843)* | -5.019 | *(4.589)* |
| log(employees) | 1.025 | *(0.938)* | 1.508 | *(1.026)* | 1.847 | *(1.232)* | 2.492* | *(1.371)* |
| *States* | | | | | | | | |
| Baden-Wurttemberg | 2.908 | *(2.199)* | 2.935 | *(2.339)* | 3.272 | *(2.771)* | 3.527 | *(2.997)* |
| Berlin | 20.028*** | *(6.567)* | 20.718*** | *(6.500)* | 23.770*** | *(8.219)* | 25.392*** | *(8.240)* |
| Brandenburg | -6.748 | *(4.626)* | -4.926 | *(4.862)* | -17.098** | *(6.633)* | -15.002** | *(7.078)* |
| Bremen | 4.778 | *(9.521)* | -2.588 | *(12.095)* | 6.157 | *(11.850)* | -3.627 | *(15.569)* |
| Hamburg | -6.867 | *(9.496)* | -1.462 | *(10.423)* | -6.192 | *(11.897)* | 1.101 | *(13.236)* |
| Hesse | -0.040 | *(3.267)* | 1.586 | *(3.501)* | 0.833 | *(4.156)* | 3.091 | *(4.522)* |
| Lower Saxony | -1.582 | *(3.118)* | 0.388 | *(3.202)* | -2.288 | *(3.999)* | 0.723 | *(4.156)* |
| Mecklenburg-W. Pom. | -9.082 | *(5.677)* | -2.402 | *(6.507)* | -14.445* | *(7.704)* | -7.648 | *(9.063)* |
| N. Rhine-Westphalia | 5.786*** | *(2.135)* | 7.637*** | *(2.294)* | 7.348*** | *(2.698)* | 9.774*** | *(2.936)* |
| Rhineland.-Palatinate | -0.101 | *(4.540)* | -2.516 | *(5.012)* | 0.742 | *(5.732)* | -1.000 | *(6.499)* |
| Saarland | 17.653* | *(9.596)* | 29.101*** | *(10.572)* | 22.275* | *(11.694)* | 35.080*** | *(13.057)* |
| Saxony | -5.171** | *(2.558)* | -3.503 | *(2.641)* | -9.683*** | *(3.422)* | -7.605** | *(3.602)* |
| Saxony-Anhalt | -11.463*** | *(4.244)* | -9.512** | *(4.349)* | -15.416*** | *(5.716)* | -13.352** | *(5.987)* |
| Schleswig-Holstein | 7.504 | *(7.173)* | 6.649 | *(7.462)* | 3.171 | *(9.730)* | 1.794 | *(10.576)* |
| Thuringia | -7.273** | *(3.006)* | -6.129** | *(3.097)* | -12.378*** | *(4.025)* | -10.121** | *(4.191)* |
| *NACE Industries* | | | | | | | | |
| NACE 15/16 | -9.516*** | *(3.263)* | -8.282** | *(3.406)* | -14.616*** | *(4.398)* | -13.668*** | *(4.686)* |
| NACE 17/18/19 | 14.085*** | *(3.378)* | 15.846*** | *(3.648)* | 18.258*** | *(4.266)* | 20.967*** | *(4.667)* |
| NACE 20 | -4.577 | *(3.903)* | -2.869 | *(3.979)* | -6.130 | *(5.237)* | -4.217 | *(5.436)* |
| NACE 21 | 6.743* | *(3.582)* | 7.770** | *(3.714)* | 10.314** | *(4.484)* | 11.676** | *(4.709)* |
| NACE 22 | -16.856*** | *(3.244)* | -15.873*** | *(3.414)* | -31.251*** | *(4.707)* | -30.628*** | *(5.074)* |
| NACE 23/24 | 5.827 | *(4.477)* | 4.165 | *(4.712)* | 11.631** | *(5.639)* | 10.384* | *(6.022)* |
| NACE 25 | -4.132 | *(3.486)* | -1.921 | *(3.596)* | -6.093 | *(4.569)* | -3.009 | *(4.769)* |
| NACE 26 | 0.922 | *(3.122)* | -1.647 | *(3.285)* | -1.322 | *(4.135)* | -5.369 | *(4.491)* |
| NACE 29/30 | 21.018*** | *(2.570)* | 21.335** | *(2.705)* | 24.443*** | *(3.261)* | 25.198*** | *(3.477)* |
| NACE 31 | 5.909* | *(3.387)* | 9.072** | *(3.594)* | 8.551** | *(4.243)* | 13.201*** | *(4.541)* |
| NACE 32 | 13.901*** | *(4.556)* | 15.914*** | *(4.794)* | 14.369** | *(5.760)* | 17.098*** | *(6.130)* |
| NACE 33 | 19.490*** | *(3.652)* | 17.006*** | *(3.799)* | 23.572*** | *(4.602)* | 21.294*** | *(4.868)* |
| NACE 34/35 | 13.653*** | *(4.525)* | 11.022** | *(4.920)* | 15.044*** | *(5.624)* | 12.102* | *(6.214)* |
| NACE 36 | -3.363 | *(3.502)* | -2.101 | *(3.604)* | -2.711 | *(4.513)* | -0.437 | *(4.688)* |
| Constant | -16.333*** | *(5.343)* | -20.316*** | *(5.737)* | -36.589*** | *(7.000)* | -43.113*** | *(7.648)* |
| Observations | 981 | | 847 | | 981 | | 847 | |
| $R^2$ (adj.) | 0.384 | | 0.400 | | | | | |

Standard errors in parentheses. – Level of statistical significance: *** 1%, ** 5%, * 10%.

Residual categories of regional and sectoral dummies: Bavaria, NACE 27/28.

**Table 3: IV Regressions**

Dependent variable: export share

| | (5) | | (6) | | (7) | | (8) | |
|---|---|---|---|---|---|---|---|---|
| Innovator | 8.237*** | *(2.350)* | 5.303** | *(2.506)* | 6.836*** | *(2.500)* | 7.666*** | *(2.278)* |
| log(turnover) | 3.103*** | *(0.812)* | 3.260*** | *(0.810)* | 3.112*** | *(0.809)* | 3.095*** | *(0.810)* |
| log(employees) | 0.643 | *(0.937)* | 0.787 | *(0.937)* | 0.747 | *(0.936)* | 0.683 | *(0.934)* |
| *States, NACE, Constant* | *incl.* | | *incl.* | | *incl.* | | *incl.* | |
| Turnover missing | -0.688 | *(2.866)* | -0.799 | *(2.852)* | -0.536 | *(2.854)* | -0.59 | *(2.864)* |
| PRM missing | 1.063 | *(2.458)* | | | | | 0.585 | *(2.698)* |
| ESS missing | | | 4.452 | *(3.516)* | | | | |
| TL missing | | | -2.022 | *(3.220)* | | | | |
| LEC missing | | | | | 2.957 | *(2.772)* | 2.75 | *(2.806)* |
| LR missing | | | | | -0.98 | *(2.571)* | -1.168 | *(2.632)* |
| Observations | 981 | | 981 | | 981 | | 981 | |
| Centered $R^2$ | 0.398 | | 0.406 | | 0.402 | | 0.400 | |
| Sargan test | 0.36 | | 3.40 | | 0.76 | | 1.34 | |
| Sargan $p$-value | 0.547 | | 0.183 | | 0.683 | | 0.720 | |
| Hausman $\chi^2$ | 9.075 | | 1.462 | | 3.545 | | 8.223 | |
| Hausman $p$-value | 0.003 | | 0.227 | | 0.060 | | 0.004 | |

First Stage (dependent variable: innovator):

| | (5) | | (6) | | (7) | | (8) | |
|---|---|---|---|---|---|---|---|---|
| PRM not important | -0.448*** | *(0.034)* | | | | | -0.424*** | *(0.033)* |
| ESS not important | | | -0.216*** | *(0.035)* | | | | |
| TL not important | | | -0.164*** | *(0.034)* | | | | |
| LEC very important | | | | | -0.183*** | *(0.045)* | -0.114*** | *(0.042)* |
| LR very important | | | | | -0.154*** | *(0.048)* | -0.125*** | *(0.044)* |
| INN | -0.299*** | *(0.034)* | -0.437*** | *(0.032)* | -0.703*** | *(0.032)* | -0.397*** | *(0.037)* |
| log(turnover) | 0.020 | *(0.013)* | 0.021 | *(0.014)* | 0.020 | *(0.014)* | 0.017 | *(0.013)* |
| log(employees) | 0.013 | *(0.015)* | 0.018 | *(0.016)* | 0.026 | *(0.017)* | 0.008 | *(0.015)* |
| *States, NACE, Constant* | *incl.* | | *incl.* | | *incl.* | | *incl.* | |
| Turnover missing | -0.026 | *(0.048)* | -0.025 | *(0.050)* | -0.004 | *(0.051)* | -0.035 | *(0.047)* |
| PRM missing | 0.004 | *(0.041)* | | | | | 0.096** | *(0.044)* |
| ESS missing | | | -0.052 | *(0.062)* | | | | |
| TL missing | | | -0.061 | *(0.058)* | | | | |
| LEC missing | | | | | 0.007 | *(0.050)* | -0.047 | *(0.046)* |
| LR missing | | | | | -0.167*** | *(0.047)* | -0.180*** | *(0.044)* |
| $F$-test instruments | 329.850 | | 175.450 | | 167.050 | | 182.140 | |
| $R^2$ (adj.) | 0.528 | | 0.486 | | 0.455 | | 0.547 | |

Estimated by 2SLS. – Standard errors in parentheses. – Level of statistical significance: *** 1%, ** 5%, * 10%.

**Table 4: Further IV Results**

Dependent variable: Export share

| | (9) | (10) | (11) | (12) |
|---|---|---|---|---|
| Innovator | 7.060*** *(2.215)* | 7.571*** *(2.314)* | | |
| Innovation expenditure | | | 1.506*** *(0.437)* | 1.302*** *(0.438)* |
| log(turnover) | 3.113*** *(0.809)* | 4.240*** *(0.890)* | 3.405*** *(0.902)* | 3.395*** *(0.895)* |
| log(employees) | 0.728 *(0.932)* | -0.025 *(1.036)* | 0.819 *(1.056)* | 0.937 *(1.049)* |
| *States, NACE, Constant* | *incl.* | *incl.* | *incl.* | *incl.* |
| Turnover missing | -0.595 *(2.86)* | -4.242 *(3.155)* | -2.052 *(3.384)* | -2.086 *(3.356)* |
| PRM missing | 0.795 *(2.689)* | | 3.404 *(3.057)* | 3.491 *(3.032)* |
| LEC missing | 2.781 *(2.802)* | | -1.155 *(3.327)* | -0.979 *(3.301)* |
| LR missing | -1.171 *(2.629)* | | -0.861 *(3.024)* | -0.752 *(2.999)* |
| Observations | 981 | 779 | 847 | 847 |
| Centered $R^2$ | 0.402 | 0.412 | 0.395 | 0.405 |
| Sargan test | 9.11 | 0.80 | 0.77 | 0.44 |
| Sargan $p$-value | 0.694 | 0.848 | 0.856 | 0.932 |
| Hausman $\chi^2$ | 6.942 | 3.109 | 8.202 | 5.333 |
| Hausman $p$-value | 0.008 | 0.078 | 0.004 | 0.021 |

First Stage (dependent variable: innovator/innovation expenditure):

| | (9) | (10) | (11) | (12) |
|---|---|---|---|---|
| PRM not important | | -0.397*** *(0.034)* | -2.614*** *(0.415)* | |
| PRM slightly important | 0.330*** *(0.041)* | | | |
| PRM important | 0.388*** *(0.039)* | | | |
| PRM very important | 0.382*** *(0.052)* | | | |
| PRM ticked | 0.559*** *(0.117)* | | | |
| PRM categorical | | | | 1.052*** *(0.186)* |
| LEC slightly important | -0.024 *(0.041)* | | | |
| LEC important | -0.093** *(0.043)* | | | |
| LEC very important | -0.184*** *(0.046)* | -0.141*** *(0.041)* | -1.766*** *(0.513)* | |
| LEC ticked | -0.318*** *(0.089)* | | | |
| LEC categorical | | | | -0.721*** *(0.175)* |
| LR slightly important | 0.125*** *(0.045)* | | | |
| LR important | 0.118*** *(0.039)* | | | |
| LR very important | -0.058 *(0.050)* | -0.128*** *(0.042)* | 0.547 *(0.547)* | |
| LR ticked | -0.142 *(0.106)* | | | |
| LR categorical | | | | 0.236 *(0.183)* |
| INN | -0.419*** *(0.043)* | -0.437*** *(0.037)* | -1.878*** *(0.450)* | 1.711 *(1.731)* |
| log(turnover) | 0.018 *(0.013)* | 0.003 *(0.013)* | -0.161 *(0.168)* | -0.187 *(0.169)* |
| log(employees) | 0.004 *(0.015)* | 0.017 *(0.015)* | 0.234 *(0.193)* | 0.27 *(0.193)* |
| *States, NACE, Constant* | *incl.* | *incl.* | *incl.* | *incl.* |
| Turnover missing | -0.036 *(0.046)* | -0.078 *(0.047)* | -0.156 *(0.628)* | -0.101 *(0.630)* |
| PRM missing | 0.488*** *(0.047)* | | -0.987* *(0.590)* | 2.233*** *(0.695)* |
| LEC missing | -0.125** *(0.059)* | | 0.187 *(0.619)* | -1.638** *(0.798)* |
| LR missing | -0.071 *(0.057)* | | -0.463 *(0.581)* | 0.576 *(0.777)* |
| $F$-test instruments | 61.100 | 206.700 | 38.040 | 36.950 |
| $R^2$ (adj.) | 0.562 | 0.624 | 0.271 | 0.268 |

Estimated by 2SLS. – Standard errors in parentheses. – Level of statistical significance: *** 1%, ** 5%, * 10%.

**Table 5: IV Tobit Regression**

Dependent variable: Export share

| | (13) | | (14) | | (15) | | (16) | |
|---|---|---|---|---|---|---|---|---|
| Innovator | 10.307*** | *(2.977)* | 10.048*** | *(3.042)* | | | | |
| Innovation expenditure | | | | | 1.894*** | *(0.577)* | 1.686*** | *(0.579)* |
| log(turnover) | 4.206*** | *(1.081)* | 5.789*** | *(1.210)* | 4.732*** | *(1.227)* | 4.725*** | *(1.219)* |
| log(employees) | 1.404 | *(1.245)* | 0.451 | *(1.407)* | 1.572 | *(1.439)* | 1.708 | *(1.430)* |
| *States, NACE, Constant* | *incl.* | | *incl.* | | *incl.* | | *incl.* | |
| Turnover missing | -3.191 | *(3.864)* | -8.178* | *(4.393)* | -5.435 | *(4.721)* | -5.486 | *(4.696)* |
| PRM missing | 0.856 | *(3.476)* | | | 4.999 | *(4.022)* | 5.056 | *(3.996)* |
| LEC missing | 3.202 | *(3.610)* | | | -1.867 | *(4.389)* | -1.675 | *(4.357)* |
| LR missing | -0.708 | *(3.427)* | | | -1.027 | *(4.038)* | -0.878 | *(4.008)* |
| Observations | 981 | | 779 | | 847 | | 847 | |

Standard errors in parentheses. – Level of statistical significance: *** 1%, ** 5%, * 10%.

Estimated using Amemiya's General Least Squares (AGLS). – List of instruments: PRM, LEC, LR, INN. (13) – (15): 1 dummy each; (16): 1 categorical variable each.

**Table 6: Product versus Process Innovations**

Dependent variable: export share

| | (17) | | (18) | | (19) | | (20) | |
|---|---|---|---|---|---|---|---|---|
| | 2SLS | | | | Tobit AGLS | | | |
| Product innovator | 9.145*** | *(2.700)* | | | 12.236*** | *(3.357)* | | |
| Process innovator | | | 11.013*** | *(3.250)* | | | 14.576*** | *(4.251)* |
| log(turnover) | 3.050*** | *(0.812)* | 3.056*** | *(0.814)* | 4.147*** | *(1.083)* | 4.151*** | *(1.090)* |
| log(employees) | 0.613 | *(0.938)* | 0.467 | *(0.950)* | 1.313 | *(1.251)* | 1.131 | *(1.271)* |
| *States, NACE, Constant* | *incl.* | | *incl.* | | *incl.* | | *incl.* | |
| Turnover missing | -0.767 | *(2.866)* | -0.699 | *(2.874)* | -3.429 | *(3.867)* | -3.367 | *(3.891)* |
| PRM missing | 1.009 | *(2.664)* | 1.565 | *(2.636)* | 1.385 | *(3.435)* | 2.245 | *(3.410)* |
| LEC missing | 3.217 | *(2.805)* | 2.452 | *(2.821)* | 3.844 | *(3.610)* | 2.841 | *(3.619)* |
| LR missing | -1.214 | *(2.633)* | -0.343 | *(2.653)* | -0.788 | *(3.430)* | 0.333 | *(3.468)* |
| Observations | 981 | | 981 | | 981 | | 981 | |
| Centered $R^2$ | 0.399 | | 0.396 | | | | | |
| Sargan test | 1.338 | | 1.092 | | | | | |
| Sargan *p*-value | 0.720 | | 0.779 | | | | | |
| Hausman $\chi^2$ | 6.450 | | 6.459 | | | | | |
| Hausman *p*-value | 0.011 | | 0.011 | | | | | |

First Stage (dependent variable: product/process innovator):

| | | | | |
|---|---|---|---|---|
| PRM not important | -0.361 *** | *(0.036)* | -0.350 *** | *(0.037)* |
| LEC very important | -0.128 *** | *(0.045)* | -0.122 *** | *(0.046)* |
| LR very important | -0.078 | *(0.048)* | -0.089 * | *(0.049)* |
| INN | -0.333 *** | *(0.048)* | -0.221 *** | *(0.040)* |
| log(turnover) | 0.019 | *(0.014)* | 0.015 | *(0.014)* |
| log(employees) | 0.014 | *(0.016)* | 0.024 | *(0.017)* |
| *States, NACE, Constant* | *incl.* | | *incl.* | |
| Turnover missing | -0.011 | *(0.059)* | -0.016 | *(0.051)* |
| PRM missing | 0.032 | *(0.047)* | -0.035 | *(0.048)* |
| LEC missing | -0.095 * | *(0.050)* | -0.013 | *(0.051)* |
| LR missing | -0.144 *** | *(0.047)* | -0.190 *** | *(0.048)* |
| *F*-test instruments | 111.490 | | 74.79 | |
| $R^2$ (adj.) | 0.449 | | 0.357 | |

Standard errors in parentheses. – Level of statistical significance: *** 1%, ** 5%, * 10%.

(17) and (18): Estimated by 2SLS. – (19) and (20): Estimated using Amemiya's General Least Squares (AGLS), using PRM, LEC, LR, INN (1 dummy each) as instruments.

**Table A1: Regional Distribution of Innovative Activity**

| Bundesland | All N | Innovators N | Innovators Percent |
|---|---|---|---|
| Baden-Wurttemberg | 162 | 74 | 45.7 |
| Bavaria | 241 | 124 | 51.5 |
| Berlin | 11 | 7 | 63.6 |
| Brandenburg | 24 | 8 | 33.3 |
| Bremen | 5 | 3 | 60.0 |
| Hamburg | 5 | 3 | 60.0 |
| Hesse | 52 | 22 | 42.3 |
| Lower Saxony | 57 | 23 | 40.4 |
| Mecklenburg-West Pomerania | 15 | 7 | 46.7 |
| North Rhine-Westphalia | 172 | 85 | 49.4 |
| Rhineland-Palatinate | 24 | 11 | 45.8 |
| Saarland | 5 | 2 | 40.0 |
| Saxony | 106 | 33 | 31.1 |
| Saxony-Anhalt | 28 | 9 | 32.1 |
| Schleswig-Holstein | 9 | 6 | 66.7 |
| Thuringia | 65 | 28 | 43.1 |
| West German states | 743 | 360 | 48.5 |
| East German states | 238 | 85 | 35.7 |
| Total | 981 | 445 | 45.4 |

**Table A2: Distribution of Innovative Activity across Firm Sizes and Sectors**

No. of observations. – No. of innovators in brackets. – Percent: Innovators as percentage of total.

| NACE | | Number of employees <50 | | 50-199 | | 200-499 | | 500-999 | | 1000+ | | Total | | Percent |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 15/16 | Food products, beverages + tobacco products | 28 | [8] | 27 | [7] | 7 | [3] | 8 | [5] | 1 | [0] | 71 | [23] | 32.4 |
| 17/18/19 | Textiles, wearing apparel + leather products | 25 | [4] | 27 | [13] | 8 | [6] | 1 | [1] | 0 | [0] | 61 | [24] | 39.3 |
| 20 | Wood + products of wood | 30 | [6] | 10 | [4] | 1 | [1] | 0 | [0] | 0 | [0] | 41 | [11] | 26.8 |
| 21 | Pulp, paper + paper products | 7 | [0] | 27 | [7] | 15 | [5] | 2 | [2] | 0 | [0] | 51 | [14] | 27.5 |
| 22 | Publishing, printing + reprod. of recorded media | 27 | [9] | 28 | [15] | 9 | [1] | 3 | [1] | 3 | [1] | 70 | [27] | 38.6 |
| 23/24 | Coke, ref. petrol. prod., chemicals + chem. prod. | 11 | [6] | 12 | [7] | 5 | [2] | 1 | [1] | 0 | [0] | 29 | [16] | 55.2 |
| 25 | Rubber + plastic products | 20 | [6] | 22 | [14] | 11 | [7] | 3 | [3] | 1 | [1] | 57 | [31] | 54.4 |
| 26 | Other non-metallic mineral products | 35 | [4] | 24 | [11] | 14 | [9] | 4 | [0] | 3 | [2] | 80 | [26] | 32.5 |
| 27/28 | Basic metals + fabricated metal products | 38 | [5] | 37 | [10] | 24 | [10] | 9 | [5] | 4 | [3] | 112 | [33] | 29.5 |
| 29/30 | Machinery, equipm., office mach. + computers | 39 | [13] | 64 | [34] | 40 | [23] | 20 | [14] | 20 | [16] | 183 | [100] | 54.6 |
| 31 | Electrical machinery + apparatus | 14 | [6] | 22 | [16] | 8 | [7] | 12 | [11] | 7 | [6] | 64 | [46] | 71.9 |
| 32 | Radio, television + communication equipment | 6 | [2] | 5 | [2] | 8 | [8] | 2 | [1] | 6 | [5] | 27 | [18] | 66.7 |
| 33 | Medical, precision + optical instrum., watches | 25 | [10] | 13 | [11] | 8 | [4] | 3 | [3] | 1 | [1] | 50 | [29] | 58.0 |
| 34/35 | Motor vehicles + other transport equipment | 4 | [2] | 5 | [3] | 6 | [5] | 0 | [0] | 15 | [12] | 30 | [22] | 73.3 |
| 36 | Furniture; manufacturing n.e.c. | 21 | [5] | 17 | [8] | 14 | [10] | 2 | [1] | 1 | [1] | 55 | [25] | 45.5 |
| Total | | 330 | [86] | 340 | [162] | 178 | [101] | 71 | [48] | 62 | [48] | 981 | [445] | |
| Percent | | | 26.1 | | 47.6 | | 56.7 | | 67.6 | | 77.4 | | | 45.4 |

NACE: Nomenclature générale des activités économiques dans les Communautés européennes (General Industrial Classification of Economic Activities within the European Communities).