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Export Behavior and Firm Productivity in German Manufacturing A Firm-Level Analysis

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Export Behavior and Firm Productivity in German Manufacturing
A firm-level analysis

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Abstract

This paper analyses the relationship between firm productivity and export behavior in German manufacturing firms. We examine whether productivity increases the probability of exporting, and assert that there is a causal relationship from high productivity to entering foreign markets, as postulated by the recent literature on international trade with heterogeneous firms. In estimating productivity, we control for a possible simultaneity bias by using semiparametric estimation techniques. Moreover, we apply a matching technique in order to analyze whether the presence in international markets enabled firms to achieve further productivity improvements, without finding significant evidence for this. We conclude that high-productivity firms self-select themselves into export markets, while exporting itself does not play a significant role for productivity improvements.

Keywords: Total Factor Productivity; Exports; Export-led growth; Heterogeneous firms.

JEL-Classification: F10, F13, F14, D21, L60

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1 Introduction

Why do some firms in an industry export, while others in the same industry persistently serve the domestic market only? What are the determinants behind these different patterns within sectors? How are these differences in firm behavior related to productivity differences among firms? Do the best performers go abroad, or do firms become more productive as they serve foreign markets? This paper analyzes these questions empirically for a sample of German manufacturing firms.

In response to the empirical evidence for important heterogeneity of firms' trade orientations within sectors in recent years, a new theoretical strand of literature on international trade has begun to focus on the export behavior of firms within sectors. Melitz (2004), Melitz and Ottaviano (2003) and Bernard et al. (2003) leave behind the assumption of a representative firm for each sector and provide theoretical foundations for the relationship between within-sector heterogeneity of firms and international trade in general equilibrium. One crucial assumption of this literature is that high-productivity firms self-select themselves into export markets. This assumption implies a causal link from firm productivity to exporting, for which this paper provides an empirical test.

Being currently the largest exporter of the world, the example of Germany is of considerable interest in this context. In this paper, we are using firm-level data from a representative survey of the German manufacturing sector, the Mannheim Innovation Panel (MIP), to detect the empirical relationship between firm productivity and export status for German firms. Our data have the advantage of achieving full geographical coverage of Germany.[2] They include firms of all size classes including a considerable number of small and medium enterprises, and contain information about firms' innovative behavior. The measure for total factor productivity (TFP) used is estimated from firm input and output data, taking into account some econometric difficulties that arise in TFP estimation. Since firms observe their respective productivities that are unobserved by the researcher, they will take this knowledge into account when making their input choices –which in turn are observed and used for the estimation. As a result, there is likely to be a correlation between the error terms and the explanatory variables in the estimation of the production function, which creates a technical problem for the estimation procedure. Least-squares estimation procedures would produce biased coefficient estimates in this situation. Therefore, we estimate total factor productivity at the firm level in a way that is robust to this so-called simultaneity bias from endogenous

[2] Other studies that have used German data are Bernard and Wagner (1997), Bernard and Wagner (2001) and Wagner (2002). These authors, however, use survey data from the German state of Lower Saxony only.

input choice, by using a semi-parametric estimation technique for the production function following Olley and Pakes (1996).

Subsequently, we model the exporting decision of a firm and find that productivity increases the odds of exporting. The positive correlation between firm productivity and exporting that we find does not say anything about the direction of causality: It could be that productive firms decide to become exporters, or that exporting makes firms more productive, or both. Trying to make a clear distinction between correlation and causation, we employ the concept of Granger causality to test for causal relationships in both directions. We also document some descriptive evidence about the productivity trajectory of newly exporting firms with respect to their entry date into foreign markets.

Finally, our analysis goes one step further. To check the robustness of our results regarding the direction of causality, we explicitly test for the direction of causality opposite from the one we found using Granger causality. To do so, we employ a matching technique, in order to investigate whether exporting is at all effective for improving firm performance.[3] In examining this question, one has to take into account that the subgroup of exporting firms is not a randomly selected sample. Our previous results suggested that exporters self-selected themselves into selling abroad because they were high performers in the first place. To control for this sample selection problem, our matching technique makes inferences within pairs of firms with similar estimated a-priori probabilities of being part of the exporting subgroup. This procedure corrects for the selection bias, provided that the variables on which the matching process is conditioned account for all the systematic differences relevant to both the exporting decision and firm productivity. In other words, we explore whether an exporting firm can reap *additional* performance improvements from exposure to foreign markets.

There is an extensive debate on the relationship between openness and productivity growth using aggregate, economy-wide data. Ben-David (1993), Sachs and Warner (1995) provide empirical evidence for a positive correlation of trade and growth. Marin (1992) finds a causal link from exports to higher productivity growth for four industrial countries, including Germany. Such a causal relationship on the aggregate level can work through two channels: Either firms become more productive as they export, or increased openness initiates a process in which resources are re-allocated in favor of exporting firms that are more productive than non-exporters. Our micro-evidence that firms are unable to achieve significant

[3] Using matching techniques in the context of firm exports is relatively novel. To the best of our knowledge, only Wagner (2002) and Girma et al. (2004) have used similar methods so far.

productivity gains from exporting, is evidence for re-allocation being the primary source behind aggregate productivity gains caused by exports.

The remainder of this paper is organized as follows: The next section gives an overview over the related literature and the evidence available from other countries. Subsequently, we describe our data and give some descriptive evidence. The fourth section presents our probit estimation results concerning the determinants of exporting and the causal relation between firm productivity and export behavior. In section 5, we present the results from our matching approach, analyzing whether exporting is at all beneficial to firm performance. Finally, the last section concludes.

2 Export behavior of firms: Where do we stand?

The statement that exporters tend to outperform non-exporters is unlikely to cause much surprise among economists. In fact, apart from making intuitive sense, this insight is not new. With an increasing availability of longitudinal data at the firm level, it has been widely documented for a number of countries, both developed and developing. Micro-evidence on this issue is now available for the United States (Bernard and Jensen 1999, 2001), for Chile (Pavcnik 2002), Taiwan and Korea (Aw et al. 2000), for Colombia, Mexico and Morocco (Clerides et al. 1998), Japan (Head and Ries 2003), Spain (Delgado et al. 2002), Italy (Castellani 2001), the German state of Lower Saxony (Bernard and Wagner 2001, Wagner 2002), as well as Thailand, Indonesia, the Philippines and Korea (Hallward-Driemeier et al. 2002), Britain (Girma et al. 2004), China (Kraay 1999) and sub-saharan Africa (Bigsten et al. 2002).[4] The empirical literature finds a robust positive correlation between productivity at the firm level and exporting. The existing evidence becomes a bit thinner, however, when asks for the direction of causality between firm productivity and export status and thus goes beyond the analysis of correlation, as we do in this paper.

There are at least two prominent strands of theoretical explanations for the relationship of productivity and exporting at the firm level, each of which emphasizes one direction of the causal relationship. One approach has stressed the difficulties firms face in foreign market, due to the existence of sunk costs associated to selling abroad and fiercer competition in international markets. Roberts and Tybout (1997), Bernard and Jensen (1999) and Bernard and Wagner (2001) have found evidence for the existence of sunk costs in exporting. According to this approach, above-average performers are likely to be the ones that are able to cope with sunk costs associated to the entry into a distant market, and make positive net

[4] This list makes no claim for completeness.

profits abroad. Also, competition could be fiercer outside the home market, a feature that would again allow only the most productive firms to do well abroad. This explanation is in line with the assumption made in the theoretical literature of international trade with heterogeneous firms that high-performing firms self-select themselves into foreign markets. An alternative theoretical explanation for the firm-level link between exporting and productivity puts forward learning effects associated to exporting, implying that exporting makes firms more productive. This view appears to be particularly prominent in the management and policy literature. The possibility of useful technological and managerial inputs from international contacts is often mentioned in this context, as is the possibility of exploitation of economies of scale by operating in several markets. As far as the technological argument is concerned, one might expect the learning hypothesis to have more explanatory power for countries facing significant technological gaps vis-à-vis the foreign markets, while the economies to scale argument may be of particular relevance for firms from small domestic markets. Although the two explanations are not mutually exclusive in general, the latter one shifts the burden of the argument onto the causal relationship from exporting to productivity, whereas the former emphasizes the causal link from productivity to exporting. An empirical analysis of causality is hence a means to assess the performance of the two approaches in the data.

One of the first studies to make a clear empirical distinction between correlation and causality is Bernard and Jensen (1999). They find that exporters have all their desirable characteristics before taking up exporting, and that the performance paths of exporters and non-exporters do not diverge following the launch of export activities by the former. Using a slightly different methodology, Clerides et al. (1998) also find strong evidence for self-selection in their data from Colombia, Mexico and Morocco. They do not find any evidence for learning effects from exporting. For Taiwan, Aw et al. (2000) find that newly exporting firms outperform other firms before entry, and in some industries they experience productivity improvements following entry. Continuous exporters do not increase their productivity advantage vis-à-vis non-exporting firms over time. These results are consistent with the self-selection hypothesis, and lend only limited support to the learning hypothesis. For Korea, the correlation between export status and firm productivity is less crisp, but they find no support for the learning hypothesis here. Delgado et al. (2002) apply non-parametric methods on a panel of Spanish firms. Their results support the self-selection mechanism of highly productive firms into exporting, while the evidence for learning effects is not significant. Only when limiting their sample to young firms do they find some evidence for learning effects. On the other hand, Kraay (1999) and Bigsten et al. (2002) find evidence for learning effects for China and several Sub-Saharan African countries, respectively. Castellani (2001) finds that Italian firms with a very high exposure to foreign markets experience learning effects, while below this threshold export intensity this is not the case. In the remainder of this paper, we look for evidence both for the self-selection hypothesis and the learning hypothesis in German data.

3 Data and Descriptive Statistics

The underlying database is an extract from the Mannheim Innovation Panel (MIP), conducted by the Centre or European Economic Research (ZEW) on behalf of the German Federal Ministry for Education and Research (BMBF). With its principal focus on firms' innovation behavior, the MIP is the German part of the Community Innovation Survey (CIS) of the European Commission. Started in 1992, the representative survey collects yearly information from firms in the manufacturing sector all over the country. The survey includes firms of all size classes, including a large number of small and medium firms that are not obliged to publish their accounts by German law. This study uses an unbalanced panel of 2,149 observations on the firm level in the years from 1992 to 2000. On average, there are 5.52 years of data per firm available. Our data have the advantage of achieving full geographical coverage of Germany, including West and former East Germany. A drawback of our data set is its relatively limited size, which restricts us in our choice of methodology.[5]

The data contain information on the export value of each firm. We consider as exporters those firms that sell more than a threshold value of 5% of their turnover abroad. In the light of Germany being a highly open economy in an increasingly integrated Europe, we consider this definition adequate for the sake of identifying those firms as exporters that have a minimum interest in their activities abroad. By using this definition, we want to abstract from minimal trade relationships due to border proximity and focus instead on systematic and significant foreign sales activities. 1,260 observations belong to exporting firms according to our definition. This corresponds to 227 firms in the sample that conduct exports in every observed year, whereas 112 firms have no exports in any sample year. Table 1 shows descriptive statistics for exporting and non-exporting firms.

The first step of our analysis is to arrive at an appropriate estimate of total factor productivity (henceforth TFP) at the level of the firm. Productivity is unobservable and has to be estimated using observable factor inputs and outputs. We assume a two-factor Cobb-Douglas production function containing labor and capital, and construct our TFP measure from the

[5] As an example, applying a GMM approach following Blundell and Bond (2000) is not possible with our data.

residual of each observation in the logarithmic form of the equation. However, there is a technical caveat in this estimation procedure. Using ordinary least squares methods to estimate the factor coefficients is likely to produce biased estimates, due to a correlation between the exogenous variables and the error term in the logarithmic estimation equation. The productivity of a firm -which is unobserved by the econometrician and represented by the error term in the estimation equation- is expected to influence the factor input decision, the outcome of which are the observed input factors on the right hand side of the equation. This econometric problem is commonly known as the simultaneity bias, first mentioned by Marschak and Andrews (1944).

Therefore, in line with previous studies such as Bernard and Jensen (2001a) and Pavcnik (2002), we employ a semi-parametric estimation technique following Olley and Pakes (1996) to get consistent estimates of TFP. This estimation method produces factor coefficient estimates that are robust to the presence of simultaneity and unobserved heterogeneity in production, without significantly increasing the computational burden.[6] Appendix A briefly outlines our estimation procedure for TFP. The limited size of our sample requires us to estimate the production function on a relatively high level of aggregation, dividing the manufacturing sector into four separate industries. Details of this aggregation are found in Appendix B. For the remainder of the paper, we use productivity as a relative measure, dividing it over the average level in the same year and industry at the NACE2-level. This specification allows us to focus on firm heterogeneity within sectors.

A comparison of our TFP estimates between exporters and non-exporters reveals important exporter premia in terms of productivity. In addition to our TFP estimates, our analysis uses firm size, R&D behavior and wages as well as firms' location (East or West Germany) as explanatory variables. Exporters and non-exporting firms display notable differences in those characteristics. Exporting firms are larger than non-exporting firms. On average, they have almost three times as many employees, and approximately the same holds for turnover. In our subsequent regressions, we use the log of the number of employees to account for firm size, because of the skewed size distribution of firms in our sample.

[6] The data contain no information as to whether a firm that exited the sample also left the market or not. Thus, it was not possible to control for a possible selection bias caused by non-random patterns in the exit of firms from our sample, although the methodology used would in principle allow for this.

Table 1: Descriptive Statistics of Exporters vs. Non-exporters

Variable	Exporters N=1,260	Non-Exporters N=889
TFP relative to average in industry and year	*1.09*	*0.82*
Export intensity	*0.35*	-
Number of employees	*330*	*116*
Sales in millions of Euro	*96.89*	*27.64*
Innovator (yes/no)	*0.54*	*0.26*
R&D expenditure in mio. Euro (if innovator)	*3.64*	*0.54*
R&D intensity (if innovator)	*0.04*	*0.06*
Share of sales from new products	*4.69*	*2.58*
Wage per employee	*66.27*	*53.15*
Age	*40.01*	*26.96*
East Germany	*0.22*	*0.50*

A particular advantage of our data set is that we have information on the innovative efforts of firms, which allows us to use two variables related to innovation. We include these variables to control for the importance of technology for trade flows at the firm level. Our first measure is firm expenditures in research and development. The share of firms that invest in R&D is about two times higher among the exporting firms in our sample (see table 1). The bulk of this expenditure occurs among exporting firms. Looking at R&D intensities defined as R&D expenditures as a fraction of turnover, however, reverses this picture, with the average R&D intensity being lower for exporting firms. Another variable we use is the percentage of sales that originate from products newly introduced to the market. This variable controls aspects of the product innovation activities like marketing costs that are not captured by R&D expenditures. An obvious caveat with this variable is that the definition of a new product is at the discretion of the firm itself. Having a new product may encourage a firm to expand into foreign markets. Bernard and Wagner (1997) and Bernard and Jensen (2001) use a binary variable for the introduction of new products. We prefer to use the share of sales of new products instead, on the basis that this may be a more appropriate indicator for the value of the new product to the firm. This share is considerably higher for exporting firms.

In addition, we include the average wage defined as the total wage bill divided by the number of employees. This wage proxy is the only information that we have about skill composition of a firm's labor force. In competitive factor markets, the quality of labor is positively related to the wage. At the same time, however, TFP also as a positive influence on wages, and we are unable to disentangle the two effects on wages. In our sample, exporting firms pay higher average wages, suggesting an extended use of skilled labor among exporters.

The particular situation of Germany with its turbulent recent history calls for the inclusion of a dummy variable for the formerly socialist part of the country. Since the 1989 fall of the Berlin wall, East Germany has been undergoing a transition process from a planned economy into a market economy. Several empirical investigations indicate that the transition process has not concluded yet.[7] A dummy for East German firms captures the differences caused by firm location. Table 1 shows that the group of non-exporting firms contains more than twice as many East German firms as the group of exporters.

Finally, the data contain information on the firm age. Generally, firm age has the problem of being correlated with several other variables we use, such as size, wages and productivity. Moreover, a firm may have undergone ownership changes, implying that the concept of continuity that one would suppose behind firm age may be badly represented by this variable, particularly at the upper end of the age distribution. Also, a firm is unlikely to gain more experience once it has reached a certain threshold age. For relatively young firms, however, age may be important. This is why we use age as a binary variable indicating the lower third of the age distribution, situated at approximately 10 years of age. We return to this issue in the discussion of our regression results in the next section.

4 What characterizes an exporting firm?

The next step of our analysis is to identify those firm characteristics that make a firm more likely to export. In other words, we are interested in the dividing line between firms that sell only domestically and those that export to foreign markets. Our theoretical model behind the export decision of a firm is straightforward. In the absence of sunk costs, a rational profit-maximizing firm exports if the current expected revenues from foreign sales exceed the cost of production and shipping for the foreign market. Whether or not this is the case for an individual firm is assumed to depend, among other things, on a vector of firm-specific characteristics X. In any period, a firm will export whenever exporting carries an additional positive net profit:

$$p_{it}\ q_{it}\ - c_{it}\ (X_{it}, q_{it}\ ) - S \cdot (1 - Y_{it-1}) > 0 \quad \text{for the foreign market,}$$

[7] See Czarnitzki (2003) as an example.

where p is the export price, q the exported quantity, c are additional production costs of producing q, S are sunk costs of exporting and Y is a binary variable indicating whether a firm exports or not.

If there are sunk costs involved in taking up export activities, a dynamically maximizing firm will look beyond the present period when deciding whether to export. The presence of sunk costs makes the decision rule dynamic, because exporting today carries an additional option value of being able to export tomorrow without paying the sunk costs of exporting. The value function of this dynamic problem can be expressed as:

$$V_{it} = \underset{Y \in \{0,1\}}{\max} \left(p_{it} \cdot q_{it} - c_{it}(x_{it}, q_{it}) - S \cdot (1 - Y_{it-1}) + \delta \cdot E(V_{it+1}) \right)$$

where delta is a discount factor. The solution to this problem is the decision rule

$$Y_{it} = \begin{cases} 1: & p_{it}\ q_{it}\ - c_{it}\ (X_{it}, q_{it}\ ) + \delta \cdot \left[E(V_{it+1} \mid Y_{it} = 1) - E(V_{it+1} \mid Y_{it} = 0) \right] > 0 \\ 0: & otherwise \end{cases}.$$

The last term of this expression represents the option value of exporting. In this decision rule, the firm- and time-specific realizations of the vector X determine different decision outcomes across firms and time. In other words, we are explaining different export decisions by firms with observation-specific firm characteristics. Particularly, we are interested in the effect of firm productivity as one element of that vector. If the option value due to sunk costs is indeed taken into account in the decision, we should also expect lagged values of the dependent variable to have explanatory power in the empirical implementation of this model. In order to estimate the export decision, we translate the theoretical model into an empirical probit model in which export behavior depends on a variety of observed, firm-specific characteristics:

$$P(Y_{it}=1)=\Phi(TFP_{t-1}, size_{t-1}, RD_{t-1}, NP_{t-1}, skills_{t-1}, east, young, D_{it})$$

where Φ is a normal cumulative density function, TFP is our estimated (relative) total factor productivity, size is proxied by the logarithm of employees, RD are expenditures in research and development as a fraction of turnover, NP captures the introduction of new products by a firm as explained in section 3, skills are proxied by average wages, east is a dummy for the formerly East German states and young is proxying age in the form of a binary variable indicating the lower third of the age distribution. All variables on the right hand side are lagged one period. Finally, we also include dummy variables for the sector and the year of observation to capture time- and industry-specific effects not specific to an individual firm.[8] Bootstrapped standard errors are used to test the significance of the coefficients. We are estimating two different specifications of the above equation. First, we take our entire sample in the first column of table 2. In a second glance, we look only at the subsample of firms that do not switch export status and abstract from the lagged dependent variable to check for the robustness of our previous results.

The estimation results for the whole sample identify several variables with significant explanatory power for the export decision. Sunk costs are a key determinant of the export decisions for the firms in our sample. In quantitative terms, this effect is very large: A discrete change from zero to one in the lagged export status increases the estimated probability of exporting by 80%, at the means of all remaining variables. These results are in line with the findings in Roberts & Tybout (1998) and Bernard and Wagner (2001). Another variable with a significant positive influence on the export decision is, as expected, firm productivity. The coefficient is positive and different from zero at a confidence level of 93%, implying that high-productivity firms are significantly more likely to be exporters. A larger firm size also makes a firm more likely to export. Moreover, the effort a firm puts into R&D increases the odds of exporting, while the same does not hold for the share of new products in this specification of the model. Hence, one of our innovation variables has significant explanatory power for the export behavior of firms here. Firms located in the East of Germany are significantly less likely to export, suggesting that they are still lagging behind with respect to competitiveness in international markets. The quantitative effect of location is considerable: At the means of all other variables, location in the East reduces the probability of exporting by almost 12 percentage points. Even for a firm with high productivity, the negative impact of location in the East hardly diminishes.

In a second specification of our probit model, documented in the second column of table 2, we repeat the estimation for only those firms with persistent export behavior in our sample, which excludes the lagged dependent variable from the set of regressors. We are aware of the fact that this is a somehow arbitrary selection, since firms that we observe as non-switchers of export status may indeed switch inside our time window. Restricting our attention to this subsample, however, enables us to abstract from the effect of sunk costs. As it turns out that past exporting has a remarkably strong explanatory power for the current realization of the export status, this selective specification allows us to check for the

[8] Due to the limitations of our data, the industry dummies have to be highly aggregated. We use four different industry dummies for the manufacturing sector each year. See appendix B for details on the aggregation used.

robustness of the effects of the remaining explanatory variables in our model.

Table 2: Probability of Exporting

Probit Estimates	Complete Sample	Only non-switchers
Dependent Variable: Export Status	N=2,037	N=1,369
TFP	*0.15**	*0.25****
	(1.84)	*(2.60)*
Lagged Export Status	*2.61****	-
	(29.89)	
Size (log of employment)	*0.12****	*0.53****
	(3.73)	*(14.68)*
R&D-Intensity	*2.01****	*11.27****
	(2.79)	*(6.65)*
New Product Share	*0.003*	*0.008**
	(0.78)	*(1.84)*
Average wage	*0.91*	*5.52***
	(0.37)	*(2.22)*
East Germany	*-0.31***	*-1.09****
	(-1.96)	*(-6.40)*
Young	*0.24*	*0.35***
	(1.58)	*(2.16)*
Year Dummies	*Included.*	*Included.*
Industry Dummies	*Included.*	*Included.*
Pseudo-R2	*0.61*	*0.38*

All explanatory variables are lagged one year.
Z-values in parentheses, based on bootstrapped standard errors.
, **, * indicate statistical significance at the 10%, 5% and 1% level, respectively.*

The results from this specification are qualitatively very similar to the previous ones, with generally higher levels of statistical significance of the coefficient estimates. Again, productivity significantly increases the odds of exporting, as do firm size and R&D intensity. The share of new products in a firm's product portfolio is now a significant predictor of the export status, with a positive effect on exporting. Moreover, the model predicts higher chances of exporting for firms with high-skilled employees, proxied by a high average wage. We are aware of the fact that our proxy is not a perfect one, since it is likely to be correlated with TFP, but we do not avail of any better proxy for skills. Concerned about the correlation between two of our regressors, we ran the estimation without the wage-variable, and found the results very similar to the ones reported in table 2.

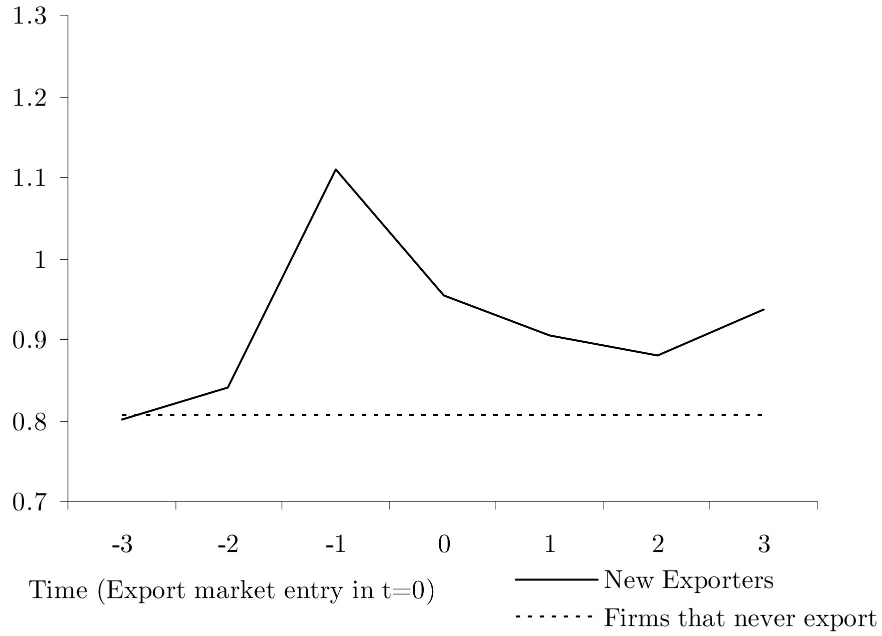
As for the complete sample, our estimation suggests that firms located in the formerly socialist part of Germany are significantly less likely to export. Finally, we are using age as a binary variable indicating the lower third of the age distribution. This formulation is due to several reasons: We are concerned about a correlation of age with several other variables in the regression, such as firm size, wages or productivity. Moreover, while we do observe age, we do not observe whether there has been continuity in ownership or management over a firm's lifespan. Some of the firms in our sample are aged well above 100 years, and it is doubtful whether age conveys any relevant information for the export decision at this high end of the distribution. On the other hand, for young firms age may well have a relevant influence. Therefore, we use a binary variable for the lowest third of the age distribution, which turns out to be 10 years.

We interpret the positive coefficient as suggesting the existence of some firms that were founded with an immediate focus beyond the domestic market. It could be the case that this result reflects the increasing degree of European trade integration at the end of the twentieth century, culminating in the 1992 Maastricht Treaty. Due to the large amount of turbulence in East German manufacturing following the German reunification, there is a disproportionate share of young firms in East Germany. Still, our coefficient estimates display opposite signs for the respective binary variables indicating young firms and East German firms. This suggests that our firm age specification indeed captures an independent influence of age on the firm export decision. Age turned out to be insignificant in any other form (linear, quadratic, or other dummy and spline combinations).

We retain as one key result from the model of the export decision that more productive firms are more likely to be exporters. Having ascertained this, we are now interested in the direction of causality between the two variables. As a first glance, we document some descriptive evidence of the relationship between firm productivity and export status across the time dimension. For this purpose, we have singled out the firms that initiated export activities during the time frame of observation. Figure 1 depicts as a bold line the trajectory of the relative productivity measures of these firms (with respect to the average in the same year and NACE2-sector). Each of them took up exporting at time t, which of course represents different years across the observations. As a means of comparison, the figure also depicts (as a dotted line) the average productivity of firms that persistently serve the home market only.

At time t-3, the future export starters are part of the group of non-exporters, although we know that they will emerge from this group and take up exports in three years to come. Their average productivity at t-3 is almost equal to the one of those firms that will not take up exporting later

Figure 1: TFP Trajectory of New Exporters



on. In the two periods preceding the export market entry, future exporters experience a significant increase in TFP, but this tendency does not continue after export market entry. Once they are exporters, these firms continue to have an average productivity above the average TFP of continuous non-exporters, but the productivity gap with respect to the latter does not widen any further, and the growth tendency is not maintained. Unfortunately, the limited size of our data does not allow us to make formal inferences between the two subgroups depicted in figure 1.[9] Still, we interpret these patterns as descriptive evidence that our new exporters may well have taken their initial export decision in reaction to their performance trajectory, while it is unlikely that their TFP benefited largely from the export decision itself.[10]

In order to make a formal test of the causal relationship between productivity and exporting, we use the concept of Granger causation: A variable X is said to granger-cause a variable Y if lagged values of X can help to predict current values of Y significantly better than own lagged

[9] Such a comparison is the basic approach for causal inference in related studies such as Bernard and Jensen (1999), Clerides et al. (1998), or Aw et al. (2000).

[10] It seems remarkable that firms actually loose some of their productivity advantage as they take up export activities. The reasons behind this fact could be an interesting topic for further research, although our data do not allow us to go much deeper on this observation.

values of Y. For this reason, we estimate two separate vector auto-regressions of productivity and exporting, using fixed effects to capture unobserved heterogeneity among firms:

$$TFP_{it} = \sum_{j=1}^{2} \beta_j^1 \cdot TFP_{it-j} + \sum_{j=1}^{2} \gamma_j^1 \cdot Y_{it-j} + \kappa_i^1 + \varepsilon_t^1$$
$$Y_{it} = \sum_{j=1}^{2} \beta_j^2 \cdot TFP_{it-j} + \sum_{j=1}^{2} \gamma_j^2 \cdot Y_{it-j} + \kappa_i^2 + \varepsilon_t^2$$

In other words, we estimate a linear model of the influence of lagged values of productivity and export status on current firm productivity, allowing for firm-specific means, and a linear probability model of the export status on its lagged values and those of productivity, allowing again for firm-specific means. Since our descriptive evidence in figure 1 suggests that most of the movement in the productivity trajectory of firms takes place in the two periods preceding export market entry, the use of two lags in the VAR estimation appeared to be the most obvious choice here. Due to the heteroscedasticity present in linear probability models, we use Huber/White/Sandwich robust standard errors in both equations. Subsequently, we perform Wald-tests to test the joint significance of the coefficients of the two lagged values of the variable that is not on the left hand side of the respective regression.

As shown in table 3, the lagged values of productivity have significant explanatory power for predicting current export status; the coefficients are jointly significant at the 5%-level. On the other hand, lagged values of the export status do not have significant explanatory power for predicting current productivity at any conventional level of statistical significance. This leads us to the conclusion that productivity granger-causes exporting in our data, while the opposite is not true.[11]

Table 3 : Testing for Granger Causation

Dependent Variable	Null hypothesis	F-Statistic
TFP_t	(1) $Y_{t-1}=0$	$F(2,1235) = 0.28$
(Current Productivity)	(2) $Y_{t-2}=0$	Prob > F = 0.75
Y_t	(1) $TFP_{t-1}=0$	$F(2,1312) = 3.12$
(Current export status)	(2) $TFP_{t-2}=0$	Prob > F = 0.04

[11] In statistically correct language, our results imply that we cannot exclude Granger non-causation from exporting to productivity, while we can exclude non-causality from productivity to exporting at a confidence level of 95%.

We have checked this result for robustness to the specification of variables used here. In particular, we have used formulations with two continuous variables (export intensity and productivity), with two binary variables (above average productivity and export status), and used conditional logit models with fixed effects instead of linear regression models where the dependent variable was binary. We have also used the absolute estimates of productivity instead of the relative ones we use throughout the paper, and changed the number of lags to one or three. The qualitative results remain unchanged throughout.

5 Does Exporting improve productivity at all?

The results from the preceding section speak quite a clear language: Our data exhibit a causal relationship from firm productivity to export status in the Granger sense. In order to check the robustness of this result, this section turns the perspective around and looks for a causal link working in the opposite way. We are now interested in examining whether there is any causal relationship at all from exporting towards productivity that we may not have detected with the method applied above. If our previous results are robust, we should not be able to detect such a causal link. This section employs a matching technique to make consistent comparisons between exporters and non-exporters in our sample, regarding TFP in levels and growth rates. Our aim is to assess the causal effects of a treatment, exporting, on the treatment group, the exporting firms.[12]

This setup bears close resemblance to situations encountered in the microeconometric evaluation of active labor market policies, as surveyed in Heckman et al. (1999).[13] In that literature, the research interest lies in identifying the causal effect of a treatment, which could be a training program. The natural variable of interest for the evaluation of the treatment is the difference between the average of an outcome variable of a treatment group that participated in a program, and the average outcome variable in the counterfactual situation of that same group not having participated. The problem is that by definition, the latter case is not observed. Comparing simple averages of a treatment group and a control group, however, produces biased results, because the selection mechanism that governs entry into the treatment group is a non-random process.

[12] See Rosenbaum and Rubin (1983) and Heckman et al. (1998) for a more comprehensive discussion of matching methods.
[13] Matching Methods have also been applied in other contexts, such as the effects of R&D subsidies on firms, e.g. Almus and Czarnitzki (2003).

Matching methods offer a solution to this “missing data problem” (Heckman et al. 1998) by undertaking comparisons between the average outcomes of a treatment and a control group conditional on a vector of observable variables X instead, where X is assumed to influence the selection decision. Each element of the treatment group is appropriately matched with one (or more) elements of the control group. In this conditional sample, one can then assume that elements of both groups exhibit no systematic differences relevant to the selection process, a statement that can not be made unconditionally. Hence, while there is no control element with which one could compare a treated element unconditionally, matching techniques assume that one can undertake such comparisons conditional on the observed realizations of X. All comparisons are hence made within the matched pairs, and the effects of treatment averaged over all elements of the treatment group. The so-calculated effect of the treatment variable is called the average treatment effect on the treated, and can be given a causal interpretation.

Of course, applying a matching technique requires that one can correctly identify the determinants of selection into the treatment group, which are the exporting firms in our sample. The empirical model of the export decision estimated in section 4 is able to classify correctly 92% of the observations into their respective export status.[14] This gives us confidence that we have identified an appropriate mapping from the observed firm characteristics into the export status. In other words, we dispose of an appropriate model for the selection mechanism to apply matching methods.

A crucial assumption for the validity of applying matching is the assumption of conditional independence. This assumption is satisfied as long as the fact that one firm takes up export activities does not affect the outcome variable (productivity) of the non-exporting firms. The result of firm productivity driving own export status and not vice versa in section 4, suggests that firm productivity is not very sensitive to own export status (the verification of which is our aim in this section), and it should be even less likely to react to the export status of other firms in the sample. Moreover, the data exhibit a persistent coexistence of exporting and non-exporting firms in the same sectors, and despite a notable amount of turbulence between these two groups, there exporters display a persistently higher productivity. Hence there is no reason to believe that the conditional independence assumption is violated in our case.

[14] Of 2037 observations, 72 were incorrectly predicted to be exporters, while 94 were wrongly predicted to serve the domestic market only. Hence our prediction errors are more or less balanced between the two types of errors possible.

Our matching technique is one-to-one, i.e. it undertakes comparisons within pairs of observations, conditional on a vector X.[15] The variables contained in this vector are the explanatory variables used the probit model of section 4, for the whole sample. Each exporting firm is thus matched with one non-exporting firm in a manner that minimizes the within-pair difference in the estimated probability of having taken up exports (the so-called propensity score). In addition to the propensity score, we decided to take firm size and location in East or West into account in creating the matched pairs, in order to guarantee some minimum level of homogeneity within our matches.[16] The matching is implemented in Stata 8 using the psmatch2 procedure by Leuven and Sianesi (2003).

The matching procedure has been able to assign a match to all but 30 of the exporting firms. This is the case because we prefer a cautious formulation by not assigning a match to exporters with a higher propensity score than the highest one of a non-exporting firm to satisfy the common-support condition. A total number of 840 non-exporting firms have been assigned as matches to 1,167 firms, where a control observation can be assigned more than once in the matching process. The within-pair differences of the propensity score are quite small, with an average of 0.005 and a standard deviation of 0.043. This suggests that our matching process has been able to find appropriate matches.

Table 4 shows the averages on the outcome variables productivity and its growth rates for exporters (the treated) and non-exporters (the controls) in the first two columns. The third column contains the average difference of the outcome variable between these two groups for the unmatched sample. This is the same result obtained in table 1, i.e. a simple mean comparison between exporters and non-exporters. Looking at TFP in levels, we find that for the unmatched sample, exporters are on average more productive by about a quarter of the average TFP in each sector and year. Once one considers the inference within the matched pairs, however, this difference becomes very small, as can be seen in the rightmost column of table 4. This difference within the matched pairs is called the average treatment effect on the treated (ATT), and is the interesting result for a causal interpretation.

[15] We used a t-test to infer whether the distances to the nearest neighbors in both directions are symmetrical, in order to assure that matching with only one nearest neighbor does not introduce a bias. For 99,99% of the treatment observations, symmetry could not be rejected at the 1% significance level.

[16] The distance measure used to condition on the three variables is Mahalanobis distance.

Table 4 : Matching Results

	Treated	Controls	Diff. of sample means	ATT (Std.Dev.)
Outcome Variable: TFP				
		N=2,037		
Unmatched Sample	N=1,197	N=840		
	1.09	0.81	0.27	
Matched Sample	N=1,167	N=840		
	1.07	1.04		0.03
				(0.04)
Outcome Variable: TFP growth 1 year later				
		N=1,170		
Unmatched Sample	N=706	N=464		
	.089	0.11	-0.02	
Matched Sample	N=677	N=464		
	.089	0.10		-0.01
				(0.09)
Outcome Variable: Cumulative TFP growth 2 years later				
		N=1,170		
Unmatched Sample	N=706	N=464		
	0.14	0.16	-0.02	
Matched Sample	N=677	N=464		
	0.13	0.15		-0.01
				(0.04)

In other words, as one controls for the selection bias of the treatment group, the productivity differences between the correctly chosen objects of comparison decrease notably in our data. In order to assess the statistical significance of this remaining positive difference, we use bootstrapped standard errors. These are reported below the average treatment effects. Comparing the average treatment effect on the treated of approximately 0.03 with our bootstrapped standard error of approximately 0.04 shows that while the difference is positive, it is not significantly different from zero at any conventional level of statistical significance. Hence we conclude that once we control for the bias induced by the non-random sample selection, there are no more significant productivity advantages for exporters.

Looking at productivity growth instead of levels, we find that the average TFP growth of exporters is slightly slower than for non-exporting firms.[17] This holds whether we define the growth rates over a time frame of one or

[17] When examining growth rates of productivity, we refer to growth rates of absolute TFP rather than the relative measure we use throughout the rest of the paper. The results are qualitatively similar, however, for both TFP measures.

of two years ahead from the observation time. In other words, once a firm is an exporter, its productivity does not grow faster on average than that of an average non-exporting firm, regardless of whether one applies matching or not. Again, bootstrapped standard errors reveal that the difference is statistically insignificant. Note, however, that exporters have a higher average TFP level than non-exporting firms.

Summing up the results from the application of the matching procedure, we find that once we control appropriately for the selection into the treatment group, there are no significant causal effects from exporting towards TFP, neither in levels nor in growth rates over one or two years following the observation date. The results from the Granger causality tests in section 4 are thus confirmed by the results of the matching analysis.

6 Conclusions

In this paper, we have examined the relationship between export behavior and total factor productivity at the firm level, using a representative sample of German manufacturing firms. Firm productivities are estimated using a semiparametric estimation method following Olley and Pakes (1996). We find that those firms that serve foreign markets are above average performers in terms of productivity. In our model of the export decision of the firm, productivity increases the probability of exporting.

In order to determine the direction of causality between exporting and productivity, we estimate vector auto-regression models with fixed effects for the two variables, and run Granger-causation test in both directions. We find that exporting does not Granger-cause productivity, while in the opposite direction we do detect a causal relationship in the Granger sense. We also depict the productivity trajectory of future export starters with respect to their entry date into foreign markets, and find that these firms tend to have their desirable performance characteristics already before taking up export activities. These results suggest that the direction of causality runs from productivity to exporting, and not vice versa.

Finally, we go one step further and explicitly test for productivity gains from exporting. We use our empirical model of the export decision to predict the probability of a positive export decision for the firms in our sample. Then we compare the productivities between exporters and non-exporters, conditional on the estimated probabilities of exporting, as well as on size and on geographical location (East or West Germany). We make inferences within matched pairs of exporters and non-exporters. By employing the matching method, we control for the non-random selection of exporting firms in our sample, and interpret our results as causal. We find no significant productivity differences between exporting and non-exporting firms within the matched pairs, neither in levels nor growth rates, and conclude that there are no statistically significant productivity gains from exporting in our sample.

Our results concerning the direction of causality can hence be seen as quite robust: Causality runs from productivity to exporting, and not vice versa. The good ones go abroad, while exporting itself does not help a firm to improve its productivity. This result supports the selection mechanism assumed in recent theoretical models of international trade with heterogeneous firms (Melitz 2004, Melitz and Ottaviano 2003, Bernard et al 2002). In these models, intra-sectoral differences in export behavior are explained by exogenously different productivity levels of firms, with the high-productivity firms serving foreign markets. According to the results of our analysis, this assumption seems appropriate for the case of German manufacturing.

From an industrial policy perspective, there is hence no reason why German policy makers should prefer foreign sales over domestic sales. Where policy aims at creating new exporters that have not to date been exceptional performers, one has reason to wonder whether such firms will ever be able to survive in international markets without public support. Our results show no support for the hypothesis that firms will become better performers once they are active in foreign markets. Given the fact that Germany is generally considered a technologically advanced economy with a significant domestic market size, these results may be different for firms from other economies, where technological spillovers from exporting or economies of scale are more likely to matter.

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Appendix A. Estimation of Firm Productivities

Firm productivities are estimated assuming a Cobb-Douglas production function with labour and capital as input factors. The output measure used is firm value-added. The estimation equation (in logarithmic form) is hence:

$$y_{it} = \beta \cdot l_{it} + \gamma \cdot k_{it} + u_{it}$$

In this equation, the estimated error term u_{it} proxies the logarithm of plant- and time-specific total factor productivity. The problem usually referred to as the simultaneity problem is that at least a part of the TFP will be observed by the firm at a point in time early enough so as to allow the firm to change the factor input decision. Profit maximization then implies that the realization of the error term is expected to influence the decision on factor inputs, rendering OLS estimation inconsistent. In order to initialize the dynamic process governing inputs and error terms, we have to assume the history preceding the first observation in our sample as exogenous. Our semiparametric estimation procedure following Olley and Pakes (1996) involves two steps. In a first step, we assume that investment and capital stock are linked by the equation

$$K_{it+1} = (1-\delta)K_{it} + I_{it}$$

where K is capital stock and I is investment. Investment is then a function of the capital stock and of the part ϖ_{it} of TFP that is observed by the firm early enough to influence the investment decision:

$$i_{it} = i_t(\varpi_{it}, k_{it}).$$

Defining the inverse function $h(\ ) = i^{-1}(\ )$, we can write $\varpi_{it}=h_t(i_{it}, k_{it})$ and estimate

$$y_{it} = \beta \cdot l_{it} + \phi(i_{it}, k_{it}) + e_{it}$$

where the function $\phi(i_{it},k_{it}) = \gamma \cdot k_{it} + h_t(i_{it}, k_{it})$ is approximated by a 3rd order series estimator. The coefficient of logarithmic labour is now consistently estimated.[18] In a second step, we identify the capital coefficient consistently by estimating the equation

$$y_{it} - \beta \cdot l_{it} = \gamma \cdot k_{it} + g(\phi_{it-1} - \gamma \cdot k_{it-1}) + e_{it}$$

where g is an unknown function that is again approximated by a third order polynomial expression in ϕ_{it-1} and k_{it-1}. The consistent factor coefficient estimates allow us to construct the residuals of equation (1). In this paper, productivity is used as a relative measure, dividing the individual values over the mean of the respective NACE2-industry and year.

[18] Inverting the function i requires a monotonicity assumption regarding investment. In contrast to other firm survey data, our investment data are very complete, making this assumption seem reasonable in our case.

Appendix B. Classification of Economic Activities

Our data contains firms in the manufacturing sector, as defined by Nace-Classifications 15 to 36. This definition excludes natural-resources-based activities such as agriculture, fishing, and mining, utilities like the generation of electricity, water, recycling and the construction sector. For our estimations, we divided the manufacturing sector into 4 aggregate industries, as shown below.

NACE2-Classification of the Manufacturing Sector		Industry
15	Manufacture of food products and beverages	1
16	Manufacture of tobacco products (no observations in our sample)	
17	Manufacture of textiles	2
18	Manufacture of wearing apparel; dressing and dyeing of fur	2
19	Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, harness and footwear	2
20	Manufacture of wood and of products of wood and cork, except furniture; articles of straw and plaiting materials	2
21	Manufacture of pulp, paper and paper products	2
22	Publishing, printing and reproduction of recorded media	2
23	Manufacture of coke, refined petroleum products and nuclear fuel	3
24	Manufacture of chemicals and chemical products	3
25	Manufacture of rubber and plastic products	3
26	Manufacture of other non-metallic mineral products	3
27	Manufacture of basic metals	3
28	Manufacture of fabricated metal products, except machinery and equipment	3
29	Manufacture of machinery and equipment n.e.c.	4
30	Manufacture of office machinery and computers	4
31	Manufacture of electrical machinery and apparatus n.e.c.	4
32	Manufacture of radio, television and communication equipment and apparatus	4
33	Manufacture of medical, precision and optical instruments, watches and clocks	4
34	Manufacture of motor vehicles, trailers and semi-trailers	4
35	Manufacture of other transport equipment	4
36	Manufacture of furniture; manufacturing n.e.c.	4