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Why Exporting Matters☆

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Abstract

This paper examines productivity differences between exporting and non-exporting firms. These differences are well-documented in the literature, but less is known about the roots of these differences. We employ stochastic frontier analysis to split productivity differences into their origins, namely technical, efficiency and scale change and document these differences on the basis of a sample of Dutch firms from manufacturing and services over the period 1993-2004. We find that exporters and non-exporters are indistinguishable in terms of total factor productivity growth, however, the former systematically outperform the latter in efficiency gains and exploitation of economies of scale, but underperform in realizing technical change. Further, how much a firm exports, appears to affect only the returns to scale, while it has no significant impact on technical and efficiency change. Using matching techniques, we examine whether it is the market selection or the learning from exporting hypothesis in explaining the export-productivity nexus. We find fair support of market selection and weak support of learning and only for some types of exporters.

Keywords: productivity, efficiency, exports, stochastic frontier analysis, matching analysis
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1. Introduction

It is relatively well-established in the literature (Balassa, 1978; Edwards, 1993, 1998; Bhagwati, 1998; Frankel and Romer, 1999) that a larger export-orientation is associated with higher economic performance measured in output, value added, employment and productivity. Scores of papers link exports and economic performance and document evidence from aggregate (country-level) analyses. This result was subsequently confirmed in micro level studies for a number of countries[1]. In sum, the literature consistently

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[1] See e.g. Bernard and Jensen (1999, 2004) on the US; Bernard and Wagner (2001), Arnold and Hussinger (2004) and Wagner (2002, 2007) on Germany; Clerides et al. (1998) on Colombia, Mexico and Morocco; Kraay (1999) on China; Aw et al. (2000) on Taiwan and Korea; Pavcnik (2000) on Chile; Isgut (2001) on Colombia; Castellani (2002) on Italy; Hallward-Driemeier et al. (2002) on Thailand, Indonesia, the Philippines and Korea; Delgado et al. (2002) on Spain; Girma et al. (2004) on UK; Head and Ries (2003) on Japan; Bigsten et al. (2004) on Sub-Saharan Africa; Blalock and Gertler (2004) on Indonesia; Van Biesebroeck (2005) on African countries; and De Loecker (2007) on Slovenia. See Girma et al. (2004) for a recent survey on the empirical literature and Melitz (2003) and Bernard and Jensen (2004) for theoretical developments. Table A.6 in the appendix presents a more complete overview of methods and results in this literature.

finds support for the conclusion that "trade, especially, exports, is one of the most important ways for countries to obtain knowledge from abroad" (see World Bank, 1998, pg. 18). The direction of causality between exporting and performance, however, remains to be established.

Two hypotheses have been put forward to explain the robust positive correlation between firm exports and performance. The *learning hypothesis* argues that export activity exposes firms to the rigorous and unforgiving discipline of global competition and argues that this forces firms to shape up or shut up. The literature lists a number of sources of learning: First, exporters may learn from their presence in the export markets due to international contacts with buyers. For instance, the purchase of an input requires some degree of customization or extended coordination with the buyer having strong incentives to transmit knowledge to the supplier.[2] Second, international demand implies a higher utilization of capacity and allows the exploitation of economies of scale. Finally, exporting firms are subjected to the more intense competition in export markets. While non-exporting firms can insulate themselves from world wide competition, exporting firms can not survive without cutting slack and adopting the best practices in technology. The learning view is closely related to the 'learning-by-doing'- (Young, 1991; Chuang, 1998) and management literature. In this hypothesis entry into export markets forces firms to cut costs and become lean and mean and the causality runs from exports to performance.

The alternative explanation is the *self-selection hypothesis*. A straightforward reason to expect selection and consequently a positive correlation between exporting and performance is the existence of sunk costs. These entry costs are associated with overcoming additional costs of selling goods to foreign markets, e.g. market research costs, transportation costs, expenses related to establishing a foreign distribution channel, production costs related to product modification for foreign tastes and so on. All these extra costs provide an entry barrier and only firms with marginal costs below some threshold will "self-select" and rationally choose to enter export markets. Even if the competitive pressure is the same in domestic and foreign markets, differences in sunk entry costs can thus explain productivity differences between exporters and non-exporting firms[3] Testable implications of these models are that firms that enter export markets should outperform their domestic competitors prior to foreign market entry and firms that quit exporting should underperform relative to those that continue, sometime before their actual exit from foreign markets. The self-selection hypothesis asserts that only the most efficient and competitive firms can actually enter export markets and hence the positive correlation is due to the fact that better performance enables firms to engage in export activity, establishing the causality from performance to exports.

It is hard to settle the debate on the basis of the empirical evidence collected to date[4]. And this should perhaps also not be expected, as the two hypotheses are not mutually exclusive, empirically hard to distinguish and it is likely that both contribute to the explanation of the facts. But for policy design it obviously matters a great deal what the relative importance of these explanations is in different industries. For instance, should policies be targeted at encouraging (all) firms to enter the export market such that competition induces learning or should policies target support at firms which are already active in foreign markets, to avoid throwing good money after bad and back the winners?

In this paper we aim to shed some new light on this issue. The first purpose of this paper is therefore to trace the productivity differential between exporting and non-exporting firms to its root causes. Productivity differences among firms can come from a host of sources, and the sources of the productivity differential may already reveal something about the direction of causality that we are after. To measure and

[2] Pack and Saggi (2001) develops a model where the sellers have the incentive to provide technology to buyers, even if that technology may spill over to other sellers and buyers.

[3] Bernard and Jensen (2004); Bernard et al. (2007); Melitz (2003); Helpman et al. (2004); Yeaple (2005) developed models to propose this explanation in line the newly developed theoretical literature on international trade with heterogeneous firms and with models of industry dynamics that discuss entry, exit and productivity differences at the firm level such as e.g. Jovanovic (1982); Hopenhayn (1992); Ericson and Pakes (1995).

[4] For instance, the studies of Bernard and Wagner (1997); Bernard and Jensen (1999); Bernard and Wagner (2001); Bernard and Jensen (2004), Clerides et al. (1998), Delgado et al. (2002), Isgut (2001), Wagner (2002, 2007), Girma et al. (2004) and Arnold and Hussinger (2004) conclude in favor of the self-selection, while the studies of Kraay (1999), Castellani (2002), Bigsten et al. (2004), Blalock and Gertler (2004), Van Biesebroeck (2005) and De Loecker (2007) of the learning explanation. The study of Aw et al. (2000) finds evidence supporting of learning in Taiwan, but not in South Korea while the study of Delgado et al. (2002) reports weak evidence of learning only when it limits its sample to young firms.

decompose productivity differences, we estimate a stochastic frontier production function that can distinguish between technical change, efficiency gains and returns to scale as the sources of higher productivity[5]. This is obviously not possible in more conventional approaches, where productivity (change) is calculated as the residual of growth accounting procedures (Tybout and Westbrook, 2000; Castellani, 2002; Delgado et al., 2002; Arnold and Hussinger, 2004). To illustrate the relevance of our method, our paper analyzes productivity differentials in a large panel of Dutch firms over the period 1991-2000. There is of course already some micro-evidence on the relationship between exporting and productivity.[6]. These studies, however, present evidence on large economies with large home markets, using one-dimensional proxies for productivity and performance. Another limitation in these studies is that their results are typically obtained for the manufacturing sector only. Our analysis illustrates a new methodology and adds a small open economy with a mature export sector, including services as well as manufacturing industries to this growing body of empirical literature. As our results will show, the distinctions between sources of productivity differential matter a great deal in explaining the performance of exporting versus non-exporting firms, are crucial in determining the relative importance of learning and selection and generalize to services.

For our sample we first show that the productivity advantage of the exporting firms indeed exists and largely comes from higher levels of efficiency and economies of scale. Interestingly we also find that the exporters actually have lower rates of technical change than the non-exporting firms in our sample. This finding is found for firms in both manufacturing and services. Then we link the productivity differential to the export intensity for exporters only and find that generally the returns to scale are correlated with the intensity of exports, but export intensity has no significant impact on the other components of the productivity differential. This implies that exporting firms, regardless of their export intensity, have an efficiency advantage over non-exporters, but economies of scale depend on the relative size of exports.

These results, interesting as they are in themselves, do not yet bear directly on the question at hand. To shed light on the learning versus self-selection hypotheses above, we therefore present two additional analyses. First we use a standard difference-in-difference specification, where exporters and non-exporters are matched on their ex ante export propensity. This eliminates, to the extent possible, all selection effects, leaving only the productivity differentials that can be attributed to learning. Our results then show that learning is particularly important for explaining the productivity advantage of established exporters that always export in our sample. For firms that started, quitted or switched between exporting and not exporting in our sample, however, all coefficients switch sign or become insignificant. This indicates that selection explains their productivity differential with the non-exporters. This reversal of sign is also present for technical change, but it is not significant. As these categories of exporters are relatively rare in the sample, and the matching is never perfect, we feel that this result is still worth considering.

In a final step we exploit the the panel structure of our data a bit more by presenting the productivity differential in its components 8 years before and after the decision to start, quit and switch into or out of exporting, respectively. The results there show that prior to starting firms on average have lower returns to scale and efficiency and higher levels of technical change, whereas post entry an exporting firm has lower technological change and higher returns to scale and efficiency. For quitting firms (relative to exporters) the results are mirrored and the evidence on switchers is, as can be expected, less pronounced.

Our results suggest a more nuanced perspective on the self-selection versus learning controversy and its implications for industrial and trade policy. Post-entry learning seems to take place in terms of efficiency gains and operating closer to the optimal scale, whereas pre-entry selection is driven mainly by advantages in technical change. Firms that export thus have a productivity advantage because to be able to start exporting they had to outperform their domestic competitors on technological development, whereas once active on global markets they outperform their domestic counterparts because competition forces them to cut slack, optimize production scale and eliminate inefficiencies. To us, this makes perfect sense and the

[5]This method to estimate and break down productivity differences was pioneered by REFS and developed further by REFS, but to our knowledge we are the first to relate the resulting components of productivity to the export behavior of firms.

[6]See e.g. Bernard and Jensen (1995, 1999) for the case of US, Bernard and Wagner (1997, 2001), Wagner (2002, 2007) and Arnold and Hussinger (2004) for Germany, Castellani (2002) for Italy, Head and Ries (2003) for Japan, Delgado et al. (2002) for Spain and Girma et al. (2004, 2007) for the UK.

policy implications are straightforward. Advanced economies should support the efforts of their domestic firms indiscriminately and have self-selection run its course, whereas countries that aim to catch up to the frontier can pursue a policy of backing their export champions. The experience in South-East Asia may serve as a case in point, although we do not explore this issue further.

The remainder of the paper proceeds as follows. Section 2 introduces our stochastic frontier model of production which allows for the breakdown of productivity differentials that is explained in section 2.3. Section 3 presents our data set and descriptives. Section 4 outlines the econometric strategy and discusses the results. Section 5 summarizes our findings and concludes with policy implications and the agenda for further research.

2. Methodology

The aim of our paper is to provide an assessment of productivity differences between exporters and non-exporters. As part of our analysis, we measure - and subsequently compare - the efficiency of firms. And since we aim to correct for possible selection bias, we measure - and subsequently control for - the propensity to export. In this section, we describe the steps needed for our analysis, and how they relate to and build upon each other. We start by outlining our estimation strategy, providing an overview of the structure of our empirical analysis. Subsequently, we describe in more detail the estimation of so-called stochastic production frontiers, and the decomposition of output growth components based upon these estimations.

2.1. Estimation strategy

In Figure A.1 in the Appendix, we present a schematic overview of the way our empirical analysis is set up. For each step in the estimation strategy, we highlight the respective sections of the paper in which the results are discussed in more detail, culminating in sections 4.1, 4.2 and 4.3, where our three research questions are answered. Also emphasized in Figure A.1 are the tables and figures that accompany each step in our empirical analysis. Always, key results are presented in the paper, with further robustness tests located in the Appendix.

Our empirical analysis itself starts with the selection of the appropriate data, described in more detail in section 3. For the purpose of our analysis, we shall require three types of variables. First and foremost, we need the ingredients for the estimation of production frontiers: the production set. For each firm-year combination at our disposal, we require output (Y), capital (K) and labor (L). We make use of the so-called 'production statistics' of the Netherlands Central Bureau of Statistics (CBS). The characteristics of the data are explored in section 3. For now, it suffices to say that we use the firm-level KLEMS data the CBS includes as part of its production statistics. These data form the basis for the Dutch part of the industry-level EUKLEMS database that is often used in growth (accounting) research (**citation here**). The data include both firms active in manufacturing and in services.

Next, we need to identify exporters from non-exporters. In principle, this is fairly straightforward: exporters are those that earn revenues from exporting. However, for the purpose of our paper, we require more granularity. We shall distinguish between four different groups of exporters: (i) those that *always* export; (ii) those that *start* to export at some point during our sample period; (iii) those that *quit* exporting at some point during our sample period; (iv) those that *switch* between exporting and not exporting. Distinguishing between these four groups will allow us to more clearly distinguish between learning from exporting and the fact that the most productive firms may select into exporting.

Controlling for possible selection effects, requires the use of matched samples, where each group of exporters is matched with a group of non-exporters that has the same propensity to export. In addition to a firm-level production set and export dummies, we therefore need a number of variables that we shall use to estimate export propensities, in line with (**citation here**). As explained in detail in Heckman et al. (1997, 1998), we require a set of covariates that strikes a balance between capturing what can reasonably be assumed to reflect the likelihood that a firm is an exporter, yet less than perfectly discriminates exporters from non-exporters. In this manner, we can expect to end up with with matched samples for each of our groups of exporters (always, starters, quitters and switchers), as we carry out our propensity matching for each group, in manufacturing and services, respectively.[7] We identify three covariates. First, we include the price of labor, as firms with more highly qualified personnel may be more likely to (produce superior products and) export (**citation here?**). Next, we include the size of the firm, measured by total assets, as larger firms may be more likely to expand beyond (restrictive) national borders and export (**citation here?**). Finally, we include communication expenses, as firms with large advertising budgets may find it easier to bring their products to the attention of foreign (potential) consumers, and therefore are more likely to export (**citation here?**). Section 3 contains a description of these covariates, that are included in Table 3.

The next steps in our analysis are the estimation of stochastic production frontiers for firms in each industry in our sample, and the estimation of export propensities. Whereas the former is done at the SBI2 level, the latter is done at the SBI1 level, due to computing time restrictions.[8] Details about the stochastic production frontier model are explained in the next subsection.[9] Once the frontier estimations are done, we can construct output growth components, as explained in detail in Section 2.3.

Subsequently, we answer our three questions. First, we ask whether it matters if firms export. In Section 4.1, we therefore estimate of export premia, and start by estimating the following equation:

$$g_{TFP_{ijt}} = b_j + b_{always}D_{always} + b_{starter}D_{starter} + b_{quitter}D_{quitter} + b_{switcher}D_{switcher} + \varepsilon_{ijt} \tag{1}$$

where $g_{TFP_{ijt}}$ is the TFP growth of firm i in industry j at time t. We include industry-specific fixed effects, where industries are classified at the SIC2 level, as shown in Table A.1, and we estimate the equation for both manufacturing and services, respectively. Although we start by estimating equation 1 for $g_{TFP_{ijt}}$, we subsequently repeat these estimations for each component of $g_{TFP_{ijt}}$, as derived in Section 2.3. In equation 1, we identify four different groups of exporters: (i) firms that always export; (ii) firms that start to export; (iii) firms that quit exporting; (iv) firms that switch between exporting and not exporting. Coefficients b_{always} to $b_{switcher}$ subsequently give us the export premia for each group, in line with **citation needed here**. These coefficients are shown in panels (a) and (b) of Table 4.

A straightforward interpretation of the results from equation 1 requires the assumption that firms are randomly selected to either export or not. Clearly, this assumption can easily be challenged, in which case the results from equation 1 confound learning and selection. Therefore, we subsequently estimate the propensity to export (**citation needed here**):

$$D_{always} = b_0 + b_{p_{labor}} p_{labor_{ijt}} + b_{size} size_{ijt} + b_{communication} communication_{ijt} + b_j D_j + \varepsilon_{ijt} \text{ if } D_{always} = 1 | D_{never} = 1 \tag{2}$$

where p_{labor} is the price of labor, reflecting the fact that firms that decide to export are more likely to produce high-quality products, requiring more expensive units of labor. Next, *size* is total assets, reflecting the fact that firms that decide to export may do so because their growth opportunities in domestic markets have been exploited. Finally, *communication* measures the amount of advertising and public relations expenditures of firms, reflecting the fact that firms that decide to export are more likely to engage in activities aimed at acquainting consumers with their products. D_j is a dummy for industry j, and is included for every industry expect for the base industry. Equation 2 is a standard propensity score model, which we estimate with common support (i.e., we include non-exporting firms with a propensity score within the same range as the propensity score for exporters) and kernel-based matching, to ensure that we have a close match between 'treatment' and control group. As these estimations are very computationally very

[7]To see why, consider income from abroad as a covariate: this would result in a very small control group, most likely consisting of outliers.

[8]Use of these CBS data takes place on a 'remote access' PC. The estimation of propensity scores in Stata, using the psmatch2 command is very time-consuming, due in large part to the matching itself. For the large sample used in this study, estimating the propensity scores for each industry, separately (at SBI2) level is impossible, as the remote access connection will eventually time out. Therefore, we opt for estimating for larger sub-samples (at the SBI1 level), which takes less time, and use industry (SBI2) dummies. As a robustness test, we estimate propensity scores for industries at the SBI2 level for a few industries. Propensity scores are very similar in level and (rank) correlation is high.

[9]Frontier estimations are summarized in Table A.2, detailed propensity score results are available upon request.

intensive, and since our estimations have been conducted from a remote access computer, estimations of equation 2 have been executed at the SIC1 level. For some smaller industries, we have also estimated this equation at the industry (j) level, with no significant differences in propensity scores.

For each type of exporter, we find the appropriate control group: starters are matched with firms that never export, quitters are matched with firms that always export, and switchers are matched with both firms that never export and firms that always export, respectively. As a next step, we repeat the estimation of equation 1, but now estimate this equation for each group of exporters, respectively, for both manufacturing and services, and for both TFP growth and its components. For example, for firms that always export, we estimate:

$$g_{TFP_{ijt}} = b_j + b_{always} D_{always_{ijt}} + \varepsilon_{ijt} \text{ if } ps_{always} > 0 \tag{3}$$

where ps_{always} is the export propensity score from estimating equation 2. Hence, in estimating equation 3 we only include firms that always export and firms that never do, but have a similar propensity to export. We subsequently do the same for other groups of exporters (and their respective control groups).

Our second question, dealt with in Section 4.2, concerns the question whether it matter how much you export. With this question, we aim to uncover possible productivity and efficiency effects from learning. Therefore, to answer this question, we estimate:

$$g_{TFP_{ijt}} = b_j + b_{expint} expint_{ijt} + b_{expint^2} expint^2_{ijt} + \varepsilon_{ijt} \text{ if } expint_{ijt} > 0 \tag{4}$$

where $expint_{ijt}$ is the export intensity of firm i in industry j at time t, defined as exports over value added. As before (with the exception of equation 2), this equation has been estimated for both TFP growth and its components, at the SIC2 level for both manufacturing and services, respectively.[10]

To assess whether learning takes place, we consider $\delta g_{TFP_{ijt}} / \delta expint_{ijt}$, or $b_{expint} + 2 * b_{expint^2} expint_{ijt}$, the marginal effect of export intensity on TFP growth. Depending on the sign for b_{expint^2}, this effect is either in- or decreasing in export intensity. Table 5 shows this conditional marginal effect, measured at the mean export intensity. In this Table, a + (-) sign indicates whether b_{expint^2} is positive (negative). The most important conditional marginal effects are displayed in Figure A.3 in the Appendix.

Finally, our third question, whether it matters how long you export, is answered in Section 4.3. To answer this question, we estimate:

$$g_{TFP_{ijt}} = b_j + b_{always} D_{always} + \varepsilon_{ijt} \text{ if } ps_{always} > 0, \forall t = 1, ..., 11 \tag{5}$$

where, as before, $ps_{always} > 0$ ensures that we estimate the export premium, b_{always}, comparing firms that always export with those that never export, but have a similar propensity to export.[11] We estimate equation 5 for each time period t, where - in this case only - t reflects the time that has passed *since* a firm started to export.[12] In our empirical analysis, we therefore focus on starters and switchers, and report the development of b_{always} over time. If exporters learn from exporting, we expect a positive premium that increases over time.

2.2. *A Stochastic Production Frontier Model*

The key part of our analysis is to arrive at an appropriate estimate of the productivity differential. After accounting for differences in measurable inputs, the remaining differences in output are usually attributed to productivity differentials. This productivity thus captures differences in technology that allow a firm to produce more or better output with the same inputs, but also includes (in)efficiency due to underutilization of capacity, misallocation of resources and slack in production. It is not possible to measure the various components that make up a productivity differential, as they are inherently unobservable, but we can use

[10] As a robustness check, we also estimate equation 4 as a tobit.

[11] As a robustness test, we also have estimated equation 5 controling for the sampling weights derived from the propensity score matching. Results do not change significantly.

[12] As a robustness test, we also look at the 'premium' after exporting for selected groups.

a model that at least allows for inefficiency. Under the assumption that firms in the same industry operate under the same production possibilities frontier, we can decompose the productivity differential between exporters and non-exporters into technical, efficiency, scale and input differences. To do so, we estimate the production possibilities frontier in each industry in our sample by means of a stochastic frontier production model.[13] This estimated production frontier defines the maximum output achievable, given the current production technology and available inputs. The distance to this frontier measures the inefficiency of firms in that industry.

If all firms in an industry produce on the boundary of a common production set that consists of an input vector with two arguments, physical capital (K) and labor (L), output in every industry i can be described as:

$$Y^*_{ijt} = f(K_{ijt}, L_{ijt}, t; \beta) \exp\{\nu_{ijt}\}, \tag{6}$$

where Y^*_{ijt} is the frontier (optimum) level of output in industry i for all firms j in that industry, at time t; f and parameter vector β characterizes the production technology; t is a time trend variable that captures neutral technical change; and ν_{ijt} is and i.i.d. error term distributed as $N(0, \sigma_v^2)$, which reflects the stochastic character of the frontier.

Two things are worth noting in equation (6). First, the industry frontier, as it is defined, represents a set of maximum outputs for a range of input vectors. Therefore, at any moment in time, it is defined by the observations from a number of firms in a given industry, and not just from one firm as in conventional productivity approaches. Second, our modeling approach treats the frontier as stochastic through the inclusion of the error term ν_{ijt}, which accommodates noise in the data and therefore allows for statistical inference. In this respect, it fundamentally differs from other (non-parametric) frontier and data-envelopment analyses.[14]

Some firms, however, may lack the ability to employ existing technologies efficiently and therefore produce less than the frontier output. If the difference between optimum and actual (observable) output is represented by an exponential factor, $\exp\{-\upsilon_{ijt}\}$, then the actual output, Y_{ijt}, produced in each industry i, at time t can be expressed as a function of the stochastic frontier output, $Y_{ijt} = Y^*_{ijt} \exp\{-\upsilon_{ijt}\}$, or equivalently:

$$Y_{ijt} = f(K_{ijt}, L_{ijt}, t; \beta) \exp\{\nu_{ijt}\} \exp\{-\upsilon_{ijt}\}, \tag{7}$$

where $\upsilon_{ijt} \geq 0$ is assumed to be i.i.d., with a normal distribution truncated at zero $\mid N(0, \sigma_\upsilon^2) \mid$ and independent from the noise term, ν_{ijt}[15]. Efficiency, $\exp\{-\upsilon_{ijt}\}$, can now be measured as the ratio of actual over maximum output, $\exp\{-\upsilon_{ijt}\} = \frac{Y_{ijt}}{Y^*_{ijt}}$ ($0 \leq \exp\{-\upsilon_{ijt}\} \leq 1$ where $\exp\{-\upsilon_{ijt}\} = 1$ implies full efficiency).

To operationalize equation (7) one needs to specify the functional form of the production frontier. Specification tests favor a translog production function. [16] Thus, the stochastic frontier production specification function becomes:

$$\begin{aligned} \ln Y_{ijt} = {} & \beta_i + \beta_1 \ln K_{ijt} + \beta_2 \ln L_{ijt} + \tfrac{1}{2}\beta_{11} \ln K^2_{ijt} \\ & + \tfrac{1}{2}\beta_{22} \ln L^2_{ijt} + \beta_{12} \ln K_{ijt} \ln L_{ijt} + \gamma_t D_t + \\ & + \delta_{Kt} \ln K_{ijt} D_t + \delta_{Lt} \ln L_{ijt} D_t + v_{ijt} - u_{ijt}, \end{aligned} \tag{8}$$

where β_i are industry-specific fixed effects, and a general index of technical change is included through the inclusion of time dummies D_t, following Baltagi and Griffin (1988).

[13] Stochastic frontier analysis (SFA) was introduced by Aigner et al. (1977), Battese and Corra (1977), and Meeusen and van den Broeck (1977).

[14] Comprehensive reviews of frontier approaches can be found in Kumbhakar and Lovell (2000), and Coelli et al. (2005).

[15] When estimating equation (7), we obtain the composite residual $\exp\{\varepsilon_{ijt}\} = \exp\{\nu_{ijt}\}\exp\{-\upsilon_{ijt}\}$. Its components, $\exp\{\nu_{ijt}\}$ and $\exp\{-\upsilon_{ijt}\}$, are identified by the λ (=σ_u/σ_v) for which the likelihood is maximized (for an overview, see Coelli et al., 2005).

[16] We test whether a translog specification is indeed preferred to a Cobb-Douglas one. Our tests (not reported here) are in favor of the more general translog specification.

2.3. Decomposing Productivity Change

Differences in productivity obviously emerge when firms experience different rates of productivity change. The key question here is, do exporting firms differ from non-exporting firms in their rate of productivity change prior to or after their decision to start exporting. Our methodology not only allows us to investigate that question, but also allows us to identify the source of productivity differentials between exporters and non-exporters. To investigate this issue, we follow Kumbhakar and Lovell (see 2000, pg. 279) and decompose productivity change in firms into its components. These components of productivity can be identified from algebraic manipulations of the determinist part of the above presented production frontier (i.e. all terms except the error) in combination with the usual expression from the productivity change Divisia index.

Using a conventional Divisia index of total factor productivity (TFP) change the latter is defined as the difference between the rate of change of output and the rate of change of inputs, weighted by their expenditure shares:

$$g_{TFP} = \frac{\dot{Y}}{Y} - s_K \frac{\dot{K}}{K} - s_L \frac{\dot{L}}{L}, \tag{9}$$

where dotted variables refer to time derivatives [e.g., $\dot{Y} = \frac{dY}{dt}$] and s_K and s_L are the observed expenditure shares of capital and labor, respectively.

Totally differentiating the deterministic part of equation (7) we obtain:

$$\frac{\dot{Y}}{Y} = \frac{\partial \ln f(K, L, t; \beta)}{\partial t} - \frac{\partial v}{\partial t} + \epsilon^K \frac{\dot{K}}{K} + \epsilon^L \frac{\dot{L}}{L}, \tag{10}$$

where ϵ^K and ϵ^L denote the partial elasticity of stochastic frontier output with respect to the inputs, physical capital and labor with returns to scale, $\epsilon = \epsilon^K + \epsilon^L$.

Substituting (10) into (9), productivity change can now be expressed as:

$$g_{TFP} = \frac{\partial \ln f(K, L, t; \beta)}{\partial t} - \frac{\partial v}{\partial t} + (\epsilon - 1)[\frac{\epsilon^K}{\epsilon}\frac{\dot{K}}{K} + \frac{\epsilon^L}{\epsilon}\frac{\dot{L}}{L}] + [(\frac{\epsilon^K}{\epsilon} - s_K)\frac{\dot{K}}{K} + (\frac{\epsilon^L}{\epsilon} - s_L)\frac{\dot{L}}{L}]. \tag{11}$$

Equation 12 decomposes productivity changes into four components.

The first term corresponds to *technical change*, TC=$\frac{\partial \ln f(K,L,t;\beta)}{\partial t}$, where $TC > 0$ represents an upward shift of the production frontier (technical progress). This technical change can be attributed to capital augmenting technical change (TC^K), labor augmenting technical change (TC^L) or can be independent of the inputs, i.e. pure technical change (TC^P).

The second term corresponds to *efficiency change*, EC=$-\frac{\partial v}{\partial t}$, where $EC > 0$ represents a reduction in inefficiency.

The third term captures changes in *economies of scale*, SC=$\frac{\epsilon^K}{\epsilon}\frac{\dot{K}}{K} + \frac{\epsilon^L}{\epsilon}\frac{\dot{L}}{L}$. The change in scale economies can vary for two reasons: pure factor accumulation and input factor elasticities. For example, if an industry exhibits constant returns to scale, changes in the level of input factors do not influence the rate of change of output growth. In turn, if labor exhibits, for example, increasing returns to scale $\frac{\partial \ln f(K,L,t;\beta)}{\partial \ln L} > 1$, an increase in the labor force $\frac{\dot{L}}{L} > 0$ further increases the rate of change of output growth.

Finally, the last term corresponds to the *allocative efficiency*, AE=$(\frac{\epsilon^K}{\epsilon} - s_K)\frac{\dot{K}}{K} + (\frac{\epsilon^L}{\epsilon} - s_L)\frac{\dot{L}}{L}$. The interpretation of allocative inefficiency is a bit more involved. This term captures the impact of deviations of inputs' normalized output elasticities from their expenditure shares or of input prices from the value of their marginal products. The allocative inefficiency can represent either input allocative inefficiency or scale inefficiency or a combination of the two. When price information on inputs is unavailable, as it is the case here, the allocative inefficiency component cannot be calculated empirically. As a consequence, variation in allocative efficiency (change) among firms will end up in the stochastic residual. Assuming that such changes are randomly distributed with mean zero, this part drops out of the deterministic decomposition in equation (11) and it simplifies to:

$$g_{TFP} = \frac{\partial \ln f(K, L, t; \beta)}{\partial t} - \frac{\partial v}{\partial t} + (\epsilon - 1)[\frac{\epsilon^K}{\epsilon}\frac{\dot{K}}{K} + \frac{\epsilon^L}{\epsilon}\frac{\dot{L}}{L}] \qquad (12)$$

Table 1 below summarizes this decomposition for a translog production function as was specified in equation (8).

Table 1: Decomposition of Productivity Change, g_{TFP}

Measure		Calculation from Equation (**??**)
TC_{ijt}	=	$TC^P_{ijt}+TC^K_{ijt} + TC^L_{ijt}$
	TC^K_{ijt} =	$\delta_{Kt} \ln K_{ijt}$
	TC^L_{ijt} =	$\delta_{Lt} \ln L_{ijt}$
	TC^P_{jt} =	γ_t
EC_{ijt}	=	$\frac{\partial v_{ijt}}{\partial t}$
SC_{ijt}	=	$(\epsilon_{ijt} + 1)(\epsilon^k_{ijt} \frac{\dot{K_{ijt}}}{K_{ijt}} + \epsilon^L_{ijt} \frac{\dot{L_{ijt}}}{L_{ijt}})$
	ϵ^K_{ijt}	$= \beta_1+\beta_{11} \ln K_{ijt} + \beta_{12} \ln L_{ijt} + \delta_{Kt} D_t$
	ϵ^L_{ijt}	$= \beta_2+\beta_{22} \ln L_{ijt} + \beta_{12} \ln K_{ijt} + \delta_{Lt} D_t$
	ϵ_{ijt}	$= \epsilon^K_{ijt} + \epsilon^L_{ijt}$
$g_{TFP_{ijt}}$	=	$TC_{ijt} + EC_{ijt} + SC_{ijt}$

Productivity changes g_{TFP} are thus decomposed into a technical change component (TC), which reflects shifts of the production frontier; a technical efficiency component (EC), which captures movements toward (or away) the production frontier as industries absorb and implement best practice technologies and reduce (or exacerbate) technical inefficiencies; and a scale component (SC), which represents movements along the frontier.

3. Data and preliminary analysis

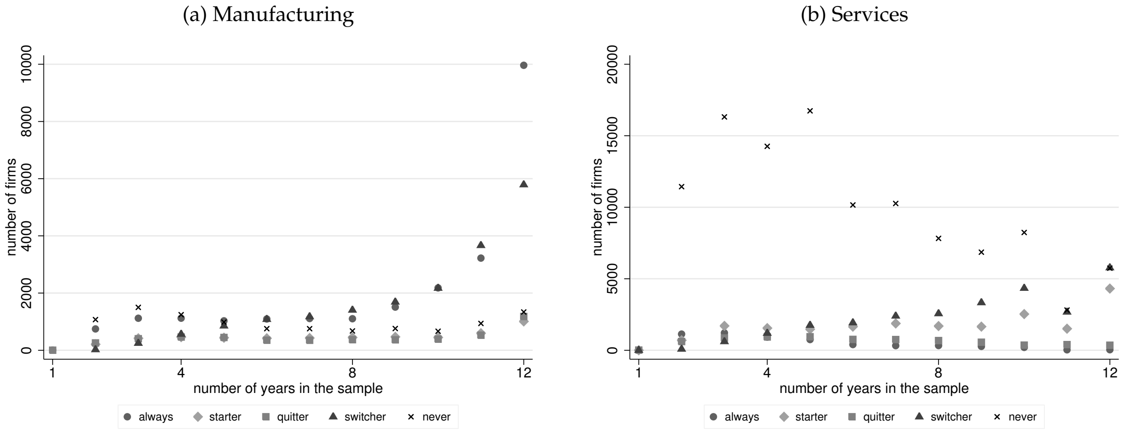
Table 2: Overview of tables. This table not in the paper, but for ourselves as help in writing

purpose	paper	companions	further robustness
descriptives	Table 3	Tables A.1, A.2 and A.3	also without fixed effects, and without truncation at μ.
export premia	Table 4	Table A.4	simple t-tests.
export intensity	Table 5	Table A.5 and Figure A.3	also estimated as tobit.
duration	Figure 2	Figure A.2	also longer, and non-matched.

Our primary data source is the Production Statistics for the Netherlands. This survey is conducted by the Netherlands Central Bureau of Statistics (CBS) and collects information from firms for the purpose of constructing the national accounts. For the purpose of our analysis, using the CBS Production Statistics (CBSPS) has a number of important advantages.

First, because the data have been collected for the purpose of aggregating to national income accounts, efforts are made to keep the sample representative. Our sample therefore covers manufacturing (64,520 observations) and services (172,558 observations) firms in all sectors and geographical regions of the Netherlands over the period 1993-2004 (see Table 3). This allows us to distinguish between firms that never export (16% of observations in manufacturing, 64% in services), firms that start to export, firms that quit and firms that switch (Table 3). This distinction shall turn out to be important, as it allows us to compare the correct groups of firms, and accurately control for the propensity to export, in order to limit sample bias. As firms in the survey are given an unique identifier, we can trace them over time if they are selected for the survey in consecutive years. Figure 1 shows that the panel structure of our sample for both manufacturing and services is such that we have a sufficiently high number of observations in all periods. In addition, Figures 1a and 1b show no evidence of attrition bias for non-exporters.

Figure 1: Sample structure



A second advantage of the CBSPS, is that it contains firm-level measures of output and inputs constructed in the same way as the EU KLEMS Growth and Productivity Accounts (O'Mahony and Timmer, 2009). Value added, capital and labor measures are all constructed along the strict guidelines described by EU KLEMS. As a result, the production set is constructed following Jorgenson et al. (1987) and Jorgenson and Grilliches (1967), "based on production possibility frontiers" (O'Mahony and Timmer, 2009, p. F376). Output Y is measured as gross output at current basic prices, capital K is measured as an index of capital services flows and labor L is an index of labor service flows.[17] Outputs are deflated using the CBSPS producer price index, and capital and labor as well as the wage sum have been deflated using the CBSPS basic price index.

The descriptives for output Y, capital K, labor L, the wage sum and export shares as well as the constructed variables Total Factor Productivity growth g_TFP, Technical Change TC, Efficiency Change EC and Scale Economies SC, are presented in Table 3. From Table 3 it is clear that most Dutch manufacturing firms are engaged in exports at least in some of the years, whereas for services this is the other way around. Substantial numbers of services firms, however, did start or switch into and out of exporting in the period of our sample (almost 36%), allowing us to still analyze the impact of exporting on productivity in the services sector. From Table 3, we also observe that exporting firms are generally speaking bigger, employ more expensive personal and invest significantly more in advertising. As explained in Section 2.1, we use these characteristics when estimating the propensity to export.

Productivity estimates in Table 3 are based on industry-specific frontier estimations, summarized in Table A.2. Interpreting the differences between output growth components in Table 3, however, requires some care: as shall be shown in the results section, there are significant differences between matched and unmatched samples.[18] Ignoring these differences for the moment, it would appear that firms that start to

[17]Note that according to this methodology, capital K is an index of capital service flows, with index weights based on the rental price of each of eight assets. The rental price in turn consists of a nominal rate of return, depreciation and capital gains. We report this measure in Table 3 and use it to estimate production frontiers. As a robustness test, we have also use built capital stocks using investment data from CBSPS and the perpetual inventory method (Hall and Jones, 1999). Using these capital stocks in our production frontier estimations does not significantly alter our results.

[18]In addition, as is common with these estimations (cf., Bos et al. (2010a,b)), standard deviations are sizeable.

Table 3: Descriptive Statistics

	Types	Unit	never		always		starter		quitter		switcher	
Manufacturing	Y	000 euro	1,906	(5,544)	11,186	(56,650)	4,326	(23,328)	3,719	(11,026)	5,125	(25,592)
	K	000 euro	315	(787)	2,459	(15,808)	1,205	(12,466)	634	(1,770)	1036	(5,845)
	L	# employed	1,231	(3,166)	6,308	(35,199)	2,450	(10,146)	2,358	(6,993)	3,001	(13754)
	price of labor	000 euro	29.271	(12.840)	35.312	(11.4003)	32.114	(10.942)	33.087	(21.230)	33.387	(12.063)
	size (total assets)	mn euro	5.228	(38.244)	37.617	(202.135)	15.447	(114.536)	10.578	(35.340)	15.263	(71.236)
	communication	000 euro	23.355	(94.395)	99.014	(519.473)	36.599	(122.211)	39.374	(129.235)	51.462	(240.905)
	export share	$/Y$	n.a.		1.941	(15.342)	0.761	(1.960)	0.707	(13.630)	0.696	(1.742)
	g_{TFP}	% p.a.	0.987	(21.894)	0.151	(20.703)	1.487	(21.801)	-0.121	(22.348)	0.906	(22.260)
	TC	% p.a.	1.475	(19,212)	0.220	(17.465)	1.487	(19.286)	0.092	(19.273)	0.914	(20.059)
	EC	% p.a.	-0.504	(11.254)	-0.188	(11.067)	-0.074	(10.646)	-0.412	(11.333)	-0.141	(9.916)
	SC	% p.a.	0.015	(2.896)	0.120	(2.352)	0.074	(2.387)	0.198	(2.897)	0.133	(2.289)
	obs	#	10,685		24,575		5,382		5,126		18,752	
Services	Y	000 euro	2,483	(16,439)	3,565	(18,226)	4,738	(18,376)	3,474	(12,219)	4,534	(17,216)
	K	000 euro	499	(4,206)	738	(4,252)	885	(4,209)	594	(3,355)	805	(4,314)
	L	# employed	1,505	(10,188)	2,022	(12,580)	2,713	(11,552)	2,269	(7,013)	2,847	(11,426)
	price of labor	000 euro	22.457	(34.910)	36.984	(26.617)	34.575	(31.197)	37.892	(18.299)	34.864	(24.465)
	size (total assets)	mn euro	4.835	(30.437)	6.628	(40.618)	8.007	(30.644)	10.220	(35.763)	9.245	(33.525)
	communication	000 euro	28.604	(263.830)	92.739	(1071.531)	71.994	(240.263)	44.800	(227.560)	72.095	(256.109)
	export share	$/Y$	n.a.		4.514	(82.065)	2.087	(11.589)	0.254	(2.388)	0.801	(6.303)
	g_{TFP}	% p.a.	1.932	(0.173)	-0.851	(0.161)	4.633	(0.277)	-1.184	(0.139)	1.432	(0.229)
	TC	% p.a.	1.994	(13.049)	-1.023	(11.186)	4.486	(25.197)	-0.856	(9.463)	1.496	(8.731)
	EC	% p.a.	-0.562	(9.940)	-0.243	(11.387)	-0.360	(10.181)	-0.880	(10.145)	-0.398	(9.695)
	SC	% p.a.	0.500	(5.528)	0.415	(2.911)	0.507	(3.542)	0.551	(3.588)	0.335	(2.664)
	obs	#	110,656		6,041		21,546		7,246		27,069	

Means (standard deviations in parentheses).

export are the most productive, both in manufacturing and in services. The most important driver for all firms appears to be technical change. Efficiency change, on average, has contributed negatively to growth over the sample period. Scale augmentation only contributes modestly in manufacturing, but appears to play a more important role in services. Perhaps not surprisingly, firms that quit exporting experience negative TFP growth, on average. In services, this is cause by both negative technical change and negative efficiency change (in equal parts), whereas in manufacturing negative efficiency change appears to be solely responsible. In Table A.3, we present the complete break-down of all TFP growth components, as well as efficiency levels for exporters and non-exporters.[19]

4. Empirical Results

In this section we first qualify the claim in the literature that exporting firms outperform the non-exporters and present the so called export premium. Our data allows us to evaluate export premia for different types of exporters and the estimation of the stochastic industry production frontiers enables us to distinguish between different sources of productivity differentials. We conclude that exporters systematically outperform the non-exporters only in efficiency gains and exploiting economies of scale. They are indistinguishable in TFP-growth and exporting firms actually underperform relative to never-exporters in realizing technical change. Then we start to probe the direction of causality between productivity gains and exporting status. A first analysis links the productivity differentials to the export intensity. If a positive link is found, then this would support the learning hypothesis, as larger export intensities can only cause

[19] Note that in this Table, all components are shown as constructed following Equation (**??**) and Table 1, whereas the main components in Table 3 are expressed in percentages per annum (i.e., multiplied by 100).

larger productivity gains through learning.[20] We show such a link for economies of scale, establishing that learning can explain productivity differentials between exporters and non-exporters to the extent that exporters learn to and are able to operate closer to their optimal scale. For the other possible sources of productivity differentials, however, this analysis is inconclusive. We therefore present the results of a difference in difference estimation, where firms in all exporting categories were matched with observationally equivalent firms in the relevant peer group. The results there show that... Finally, this section presents the results of a difference-in-difference estimation per year prior to and after the first year that the exporting firm exported in our sample. This analysis...

4.1. Does it matter if you export?

The claim that exporters outperform the non-exporters can not be substantiated for our measure of TFP-growth in Table 4.[21] This Table shows the output of simple pooled regressions of the various productivity measures on the export status of firms in manufacturing and services, respectively. In the first column none of the dummies for export status shows up significantly in a regression of g_{TFP} on a constant and dummies for export status for manufacturing. We only find a significant coefficient for starting firms in services That type, however, seems to have a *lower* rate of TFP-growth than the reference group on never-exporters. As the constant is insignificant in this regression, however, this implies that never-exporters and the other types of exporting firms are indistinguishable from each other, rendering this result an oddity in our data, possibly due to the low number of always-exporters in services.

Table 4: Export premia

(a) Manufacturing, without matching

	g_{TFP}	SC	TC	EC
always	-0.008 ***	0.001 ***	-0.011 ***	0.002
starter	0.005	0.001 *	0.001	0.003 *
quitter	-0.011 ***	0.002 ***	-0.013 ***	0.000
switcher	0.001	0.001 ***	-0.003	0.003 *

(b) Services, without matching

	g_{TFP}	SC	TC	EC
always	-0.025 ***	-0.000	-0.027 ***	0.003 *
starter	0.028 ***	0.001	0.026 ***	0.002 **
quitter	-0.023 ***	0.002 ***	-0.020 ***	-0.004 ***
switcher	-0.002	-0.001 **	-0.002	0.001

(c) Manufacturing, matched samples

	g_{TFP}	SC	TC	EC
always_{never}	-0.005 *	0.001 ***	-0.011 ***	0.005 ***
starter_{never}	-0.006	-0.000	-0.001	-0.005 **
quitter_{always}	-0.007 **	0.001	-0.004	-0.003 **
switcher_{always}	0.005 ***	0.000	0.007 ***	-0.002 *
switcher_{never}	0.004	0.001 ***	-0.001	0.004 ***

(d) Services, matched samples

	g_{TFP}	SC	TC	EC
always_{never}	-0.025 ***	-0.001 **	-0.030 ***	0.006 ***
starter_{never}	-0.024 ***	0.000	-0.021 ***	-0.003 ***
quitter_{always}	-0.038 ***	0.001 **	-0.031 ***	-0.009 ***
switcher_{always}	0.034 ***	0.001	0.038 ***	-0.005 ***
switcher_{never}	0.001 *	-0.001 **	0.000	0.002 **

The other columns in Table **??** reveal that exporters experience significantly more efficiency gains (column 3) and economies of scale (column 4) than non-exporters. Perhaps surprisingly in several cases technical change (column 2), however, appears to be less for exporting firms than it is for the never-exporters. As our measures of scale economies and efficiency gains are close to what other studies pick up when they compute overall TFP-growth using growth accounting, the results in the final columns clearly reproduce

[20]Selection could of course not be completely ruled out. If a firm is much more productive, such that it starts exporting, then it is also likely to capture a larger share of the global market, causing export intensity and productivity to be correlated. We look at productivity change, however. For the change in productivity in any given year to be positively correlated with the export intensity in that year, one would be hard pressed to square that result with the selection hypothesis.

[21]Note that our measure of TFP-growth is not the same as the one obtained from standard growth accounting exercises as we have estimated the production function allowing for inefficiency. In normal growth accounting the production function is estimated assuming that all firms produce on their efficient frontier. This may bias the various parameters in the production function. See REFS for a discussion.

the familiar result from the literature. The results in the first and particularly the second column indicate that a more careful decomposition of total factor productivity growth may well deliver some interesting qualifications to the general picture. Also the results suggest that selection and learning may well take place on different sources of productivity differentials. Note, for example, that the only group that has a positive coefficient in technical change is the starters. That result is for instance consistent with ex ante selection on the basis of technology and ex post learning in efficiency and scale. That would explain why all exporting firms except the starters have a lower rate of technological change (they already achieved a technological advantage prior to engaging in exports) and a higher rate of efficiency gains and economies of scale. To verify that conclusion, however, we need to analyze the dynamics in the data and look at rates of productivity change before and after engaging in exports.

4.2. Does it matter how much you export?

In the previous section we established a positive correlation between exporting and the productivity gains from efficiency improvement and the exploitation of economies of scale. If learning underlies this correlation, then one would expect the differential to also correlate positively with the export intensity of the firm. Exporting a larger share of the total sales implies that the firm is exposed more to foreign competition and pressure to reduce slack and produce at the optimal scale. Consequently, if learning effects are dominant in explaining the higher efficiency gains and economies of scale, then we can regress the productivity measures for all exporting firms on their export intensity. Table 5 below presents the results, where we have included a squared term to allow for a non-linear effect and TC^P, TC^K and TC^L represent pure, capital and labor augmenting technical change, respectively and EF is the efficiency level (as opposed to the efficiency change EC in the last column). The number of observations and relevant industries are listed below the exporting types in column 1. To facilitate reading we have made the cells containing positive (negative) significant coefficients for export intensity or export intensity squared dark (light) grey.

Table 5: The effect of increasing export intensity

(a) Manufacturing

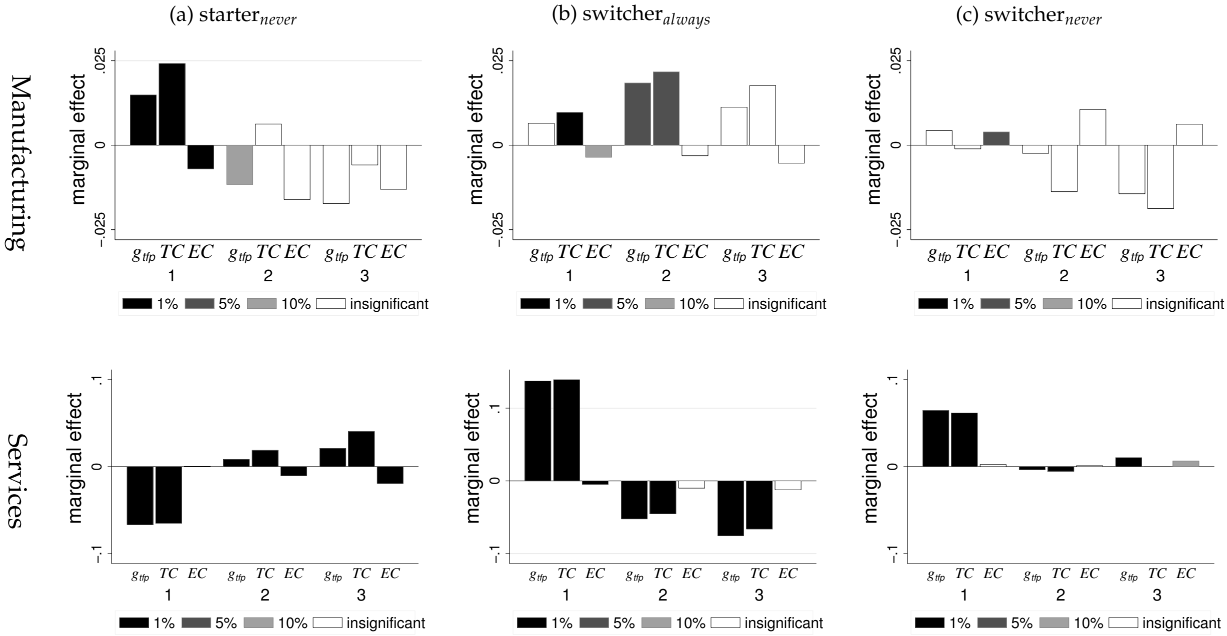
	g_{TFP}			TC			EC		
always	-0.003		$(-)$	-0.001	**	$(+)$	-0.002		$(-)$
starter	-0.015		$(+)$	-0.016		$(+)$	0.001	**	$(-)$
quitter	0.018		$(-)$	0.017		$(-)$	0.001	**	$(-)$
switcher	0.001	**	$(-)$	0.001	**	$(-)$	-0.001	**	$(-)$

(b) Services

	g_{TFP}			TC			EC		
always	0.001		$(-)$	0.002	**	$(-)$	-0.002	**	$(-)$
starter	0.006		$(-)$	0.005		$(-)$	-0.000	**	$(-)$
quitter	0.025		$(+)$	0.021		$(+)$	0.004	**	$(+)$
switcher	0.036		$(-)$	0.032		$(-)$	0.002	**	$(-)$

The Table shows that manufacturing exporters' productivity increases due to larger export intensity (linearly) only due to higher economies of scale. For services, this result is only reproduced for starters and quitters and turns out to be negative for switchers and insignificant for always exporters. As economies of scale are generally less pronounced and less important in services, this is to be expected. Moreover, the export intensity does not seem systematically correlated with higher efficiency or efficiency change. The fact that in manufacturing quitters and switchers show a positive correlation between export intensity and efficiency levels, whereas for always exporting firms the level is negative but the change is positively correlated lends some weak support towards the learning hypothesis. For services there is hardly any significant relationship. In conclusion, this analysis allows us to report some support for learning as a cause for productivity advantages due to exporting firms in manufacturing being able and stimulated to bring their operations up to the optimal scale. This, however, is a far cry from deciding the debate on learning versus selection in the literature and we proceed in the next section by accounting for selection effects in a difference-in-difference regression.

Figure 2: Export premia over time (with matched samples)



4.3. Does it matter how long your export?

The previous subsection connected learning effects to the intensity of exports and came up with very little support for the learning hypothesis. Another way to try and separate between selection and learning effects however, is to try and correct for selection effects and see what productivity differentials remain. These would then have to be attributed to learning, also shedding light on the relative importance of the two hypotheses. To this end we ran a matched difference-in-difference regression. This procedure first requires that we find a control group of firms for each exporting firm that, at least based on it observable characteristics, is equally likely to engage in exports. To this end, we estimated a probit model to construct the ex ante probability of being an exporter for all firms. Then we linked all actually exporting firms to ex ante similar firms in the relevant control group and investigate the productivity differential in its various components as before. We basically redo Table **??**, matching the exporting firms to their relevant peer group. For always exporting firms we looked for observationally equivalent firms in the never-exporting group. For the starters and quitters we looked for peers in the never- and always exporting groups respectively and for switchers we distinguished between switchers into and out of exporting (starting and quitting exports or quitting and starting exports in the period of our sample, respectively) and matched them to peers in the never and always groups, respectively. In this way, the coefficient on the dummy represents the productivity (growth) differential between the exporter and his peer group. As ex ante selection effects have thus been taken out of the equation we can trust these differentials to be the result of pure learning. Again the number of observations and relevant industries are listed in column 1 and we have shaded the cells containing positive (negative) significant coefficients on the dummies dark (light) grey to facilitate the reading of the Table.

The Table shows that in manufacturing for economies of scale, as before, the firms that always export have a significantly higher productivity than those that never export, even after accounting for selection effects. However, the signs for starters, quitters and out-switchers are now negative, whereas into-switchers are also positive. This can be interpreted as strong support for the learning hypothesis. Quitters and out-switchers underperform the always exporters as they stop or fail to learn from exports, whereas starters *underperform* relative to their peers in the never-exporting firms as they have not yet started to learn. The positive sign for into-switchers implies that even in the short span of time that these firms have exported, they have increased their returns to scale relative to never exporters significantly. For services the results on economies of scale are now similar whereas in the unmatched samples they were quite distinct. A notable difference is the out-switchers in services, that seem to outperform their peers in the always exporting group in services.

For technical change the results show that in manufacturing the quitters actually outperform the always exporters, suggesting that quitting exports frees up resources to dedicate to technology development. Other coefficients are starters against never exporters (suggesting selection on technological change if technological change is somehow slow to grind to a halt) and both types of switchers. For always against never-exporters, however the coefficient is negative, suggesting exporting firms have less time and resources to spend on making radical new technologies work. These coefficients are insignificant, however. For services the negative sign for always versus never is significant both statistically and economically and contrasts nicely with the positive sign for starters against their peers in the never exporting group. The same conclusion can be drawn from the switchers into and out of exports, where switching out of exports gives an advantage and switching into exports a disadvantage. This suggests that, more so than in manufacturing, in services technology is an important selection criterion and learning in fact has a negative impact on technical change.

For efficiency levels and efficiency gains in manufacturing the results again confirm this picture. Starters underperform against their peers in the never-exporters group whereas always exporting firms have a higher level and insignificantly lower rate of efficiency improvement relative to their peers. For quitters, interestingly, the rate of efficiency gains is higher than for always-exporters but their level is significantly lower. Apparently they quit because they cannot keep up with the competition, not because they learn less or slower. Finally, the positive coefficient for the into-switchers on the efficiency level suggests that learning effects last, even when the exporting is temporarily. In that respect it is interesting to note that the order of magnitude of the coefficient is comparable to that of the always exporting firms. For services the same pattern arises, even though none of the coefficients on efficiency change are significant. Small sample sizes may have reduced the precision of our estimates in the services sector.

5. Conclusion

This paper analyzes the productivity differences between exporting and non-exporting firms. These differences are well-documented in the literature, but less is known about the origins and causes of these differences. In this paper we apply a novel methodology to investigate firm performance in terms of productivity and its components. In a sample of Dutch manufacturing firms over the period 1993-2004 we distinguish between the always, never, starting, quitting and switching exporters and split the productivity changes in different types of technological and efficiency advantages to establish that: (i) the productivity differential can be attributed to higher levels of efficiency and returns to scale, which are more pronounced for starting then for established exporters, (iii) and always exporters have a lower rate of technical change in both services and manufacturing industries and (iv) returns to scale are concave in export intensity.

To shed light on the learning versus market selection hypotheses above, we present two additional analyses. First, we use a standard difference-in-difference specification, where exporters and non-exporters are matched on their *ex ante* export propensity. This eliminates, to the extent possible, all selection effects, leaving only the productivity differentials that can be attributed to learning. Our results then show that learning is particularly important for explaining the productivity advantage of established exporters that always export in our sample. This indicates that selection explains their productivity differential with the non-exporters. Second, we exploit the panel structure of our data a bit more by presenting the productivity differential in its components eight years before and after the decision to start, quit and switch into or out of exporting, respectively. The results there show that prior to starting firms on average have lower returns to scale and efficiency and higher levels of technical change, whereas post entry an exporting firm has lower technological change and higher returns to scale and efficiency. For quitting firms (relative to exporters) the results are mirrored and the evidence on switchers is, as can be expected, less pronounced.

Overall, results suggest a more nuanced perspective on the self-selection versus learning controversy both in manufacturing and services sector and its implications for industrial and trade policy. Advanced economies should support the efforts of their domestic firms indiscriminately and have self-selection run its course, whereas countries that aim to catch up to the frontier can pursue a policy of backing their export champions.

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Appendix

Figure A.1: Estimation strategy

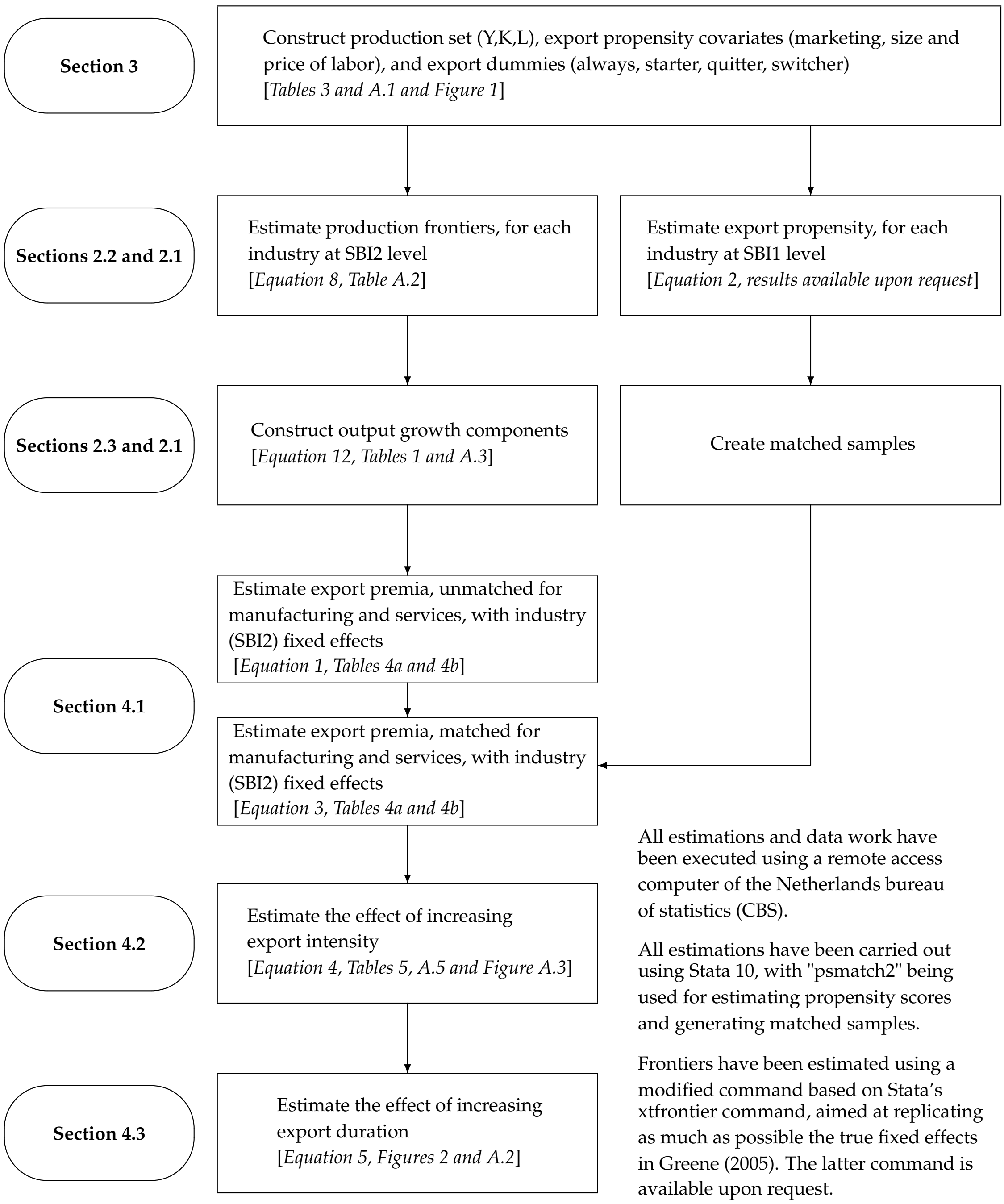

Table A.1: Descriptives per industry

	industry	SIC	Y		K		L		n
Manufacturing	Food and Drink	15	8,984	(30,702)	2,070	(6,479)	4,681	(13,229)	8,679
	Tobacco	16	12,791	(29,551)	713	(855)	2,429	(4,897)	33
	Textiles	17	3,618	(5,840)	694	(1,050)	2,354	(3,600)	1,953
	Clothing	18	1,144	(1,891)	210	(428)	826	(1,313)	1,030
	Leather and footwear	19	1,463	(1,963)	253	(365)	1,013	(1,332)	505
	Wood	20	2,271	(2,868)	390	(463)	1,578	(1,901)	2,282
	Pulp, paper & paper products	21	8,538	(12,162)	2,073	(3,984)	4,940	(6,227)	1,939
	Printing & publishing	22	5,665	(16,680)	974	(2,878)	3,273	(8,189)	7,053
	Oil	23	67,657	(140,282)	27,192	(56,161)	20,569	(34,851)	76
	Chemicals	24	23,361	(66,115)	6,253	(28,795)	10,282	(22,131)	3,170
	Rubber & plastics	25	4,795	(7,358)	1,096	(1,924)	2,889	(4,404)	3,325
	Non-metallic mineral products	26	6,651	(13,204)	1,396	(3,106)	3,610	(7,323)	2,852
	Basic metals	27	19,413	(100,267)	4,032	(22,750)	11,615	(56,130)	945
	Fabricated metal products	28	3,076	(5,918)	513	(922)	2,074	(4,192)	10,685
	Mechanical engineering	29	4,214	(8,732)	662	(3,365)	2,925	(5,556)	8,615
	Office machinery	30	18,930	(46,710)	4,307	(11,614)	13,317	(34,037)	202
	Electrical machinery	31	4,532	(9,963)	741	(1,847)	2,930	(6,310)	1,679
	Insulated wire	313	13,348	(18,630)	2,083	(2,740)	8,393	(11,011)	95
	Radio, television	32	63,016	(344,411)	14,140	(78,360)	44,877	(244,600)	424
	Scientific instruments	33	5,735	(16,279)	725	(2,909)	3,948	(12,978)	1,111
	Medical instruments	331	4,397	(15,733)	509	(1,344)	2,270	(5,124)	822
	Motor vehicles	34	10,179	(52,204)	2,810	(23,458)	5,465	(21,332)	1,459
	Other transport equipment	35	5,165	(7,885)	963	(2,169)	3,098	(4,282)	224
	Ship and boat repair	351	4,341	(9,298)	617	(1,115)	3,295	(6,549)	1,221
	Space and aircraft	353	19,607	(32,919)	4,510	(20,934)	15,173	(35,773)	98
	Furniture	36	2,684	(5,513)	471	(988)	1,743	(2,929)	3,482
	Recycling	37	1,822	(3,129)	544	(904)	839	(1,351)	561
Services	Construction	45	3,023	(10,099)	384	(1,814)	2,269	(7,476)	29,027
	Automotive	50	2,219	(6,553)	412	(1,212)	1,193	(2,696)	9,876
	Wholesale and commission trade	51	3,559	(12,224)	706	(3,059)	1,872	(6,359)	46,727
	Retail trade	52	2,646	(23,031)	649	(5,300)	1,410	(13,092)	35,691
	Hotels & catering	55	1,713	(8,255)	386	(2,004)	1,021	(6,117)	10,743
	Renting of machinery & equipment	71	4,466	(20,082)	3,181	(16,716)	779	(2,468)	3,907
	Computer and related activities	72	6,730	(35,185)	950	(5,062)	4,741	(25,545)	4,740
	Other business activities	74	3,763	(19,827)	414	(2,673)	2,768	(14,730)	27,303
	Legal, technical and advertising	7413	1,837	(3,363)	245	(464)	1,323	(2,390)	824
	Other services	93	1,026	(4,873)	253	(1,258)	568	(2,269)	3,720

Table A.2: Summary of frontier results

	sbi2	ind	lnk	lnl	lnkk	lnll	lnkl	lnkexp	lnlexp	exp	cons	Obs	μ	γ	σ^2
Manufacturing	Food and Drink	15	0.331***	0.366***	0.113***	0.14***	-0.103***	-0.035	-0.034	0.567***	1.952***	12883	-47.145***	4.936***	2.327***
	Tobacco	16	0.611	0.001	0.109	0.408**	-0.179	0.233	-1.043	1.676	3.644*	163	-0.739	-3.904	-1.405
	Textiles	17	0.509***	0.035	0.131***	0.207***	-0.147***	-0.035	0.159	-0.899	3.055***	3118	-46.072**	5.308***	2.415***
	Clothing	18	0.655***	0.153	0.138***	0.219***	-0.169***	-0.074	0.109	-0.264	1.838***	2128	-85.28	5.867***	3.275***
	Leather and footwear	19	0.261*	0.12	0.056***	0.146***	-0.056***	-0.085	0.128	-0.416	2.823***	1005	-33.061	4.901***	2.186
	Wood	20	0.458***	0.039	0.147***	0.239***	-0.161***	0.038	0.012	-0.226	2.733***	3678	-31.189	4.771***	1.737***
	Pulp, paper & paper products	21	0.624***	0.172	0.171***	0.243***	-0.194***	-0.015	-0.021	0.08	1.804***	2560	-23.65	4.414***	1.474***
	Printing & publishing	22	0.523***	0.024	0.118***	0.22***	-0.14***	-0.002	0.026	-0.12	2.6***	10712	-48.22	4.78***	2.19***
	Oil	23	1.269	-0.185**	0.309***	0.403***	-0.36***	-0.18	0.176***	0.281	0.852**	272	-13.787	20.282***	2.307***
	Chemicals	24	0.355***	0.536***	0.156***	0.213***	-0.176***	0.134	-0.24	0.971*	1.357**	4677	-39.746***	4.685***	2.547***
	Rubber & plastics	25	0.296***	0.612***	0.12***	0.15***	-0.128***	0.115	-0.131	0.325	0.939**	4990	-29.375	4.517***	1.79***
	Non-metallic mineral products	26	0.595***	0.203**	0.135***	0.205***	-0.153***	-0.015	-0.116	0.985**	1.713***	4384	-38.538	4.582***	2.263***
	Basic metals	27	0.415	0.788	0.046***	0.115***	-0.071***	-0.015	-0.381	2.556	-0.9	1408	-32.314	4.596***	1.932**
	Fabricated metal products	28	0.415***	0.106***	0.1***	0.184***	-0.111***	0.003	0.009	-0.021	2.61***	16950	-31.792***	4.576***	1.665***
	Mechanical engineering	29	0.504***	0.233***	0.139***	0.209***	-0.154***	-0.066*	0.009	0.299	1.741***	12912	-42.227	5.044***	2.151***
	Office machinery	30	1.318***	-0.573*	0.136***	0.346***	-0.247***	0.066	0.141	-1.627	3.48**	415	-65.314	5.664***	3.045**
	Electrical machinery	31	0.582***	-0.002	0.125***	0.257***	-0.178***	0.204	-0.083	-0.361	2.801***	2747	-28.967	4.074***	1.687*
	Insulated wire	313	0.608	0.27	0.128	0.274	-0.201	0.24	-0.256	1.493	0.866	248	-2.852	18.882***	0.276
	Radio, television	32	1.271	-0.256	0.083***	0.219***	-0.144***	-0.767	0.535	0.76	1.034	890	-33.208	4.794***	2.159**
	Scientific instruments	33	0.753***	0.18	0.085***	0.188***	-0.137***	-0.066	0.065	0.073	1.441**	1793	-47.674	5.017***	2.5***
	Medical instruments	331	0.534***	-0.424***	0.096***	0.276***	-0.137***	0.073	-0.034	-0.043	4.434***	1475	-36.758	5.067***	1.978***
	Motor vehicles	34	0.237**	0.596***	0.097***	0.146***	-0.105***	0.087	-0.143	0.53	0.968	2183	-21.539	4.347***	1.37***
	Other transport equipment	35	2.349	-1.835	0.134***	0.284***	-0.167***	-1.859	1.636	-0.702	4.383***	459	-34.08	4.612*	2.025
	Ship and boat repair	351	0.434***	0.314***	0.043***	0.147***	-0.079***	0.102	-0.151*	0.567	1.626***	1976	-34.341	5.182***	2.16***
	Space and aircraft	353	0.54	1.176***	0.1	0.2***	-0.158**	0.411*	-1.119***	0.21	1.41	210	-55.608	5.813	2.435
	Furniture	36	0.384***	0.117*	0.101***	0.189***	-0.11***	0.012	-0.014	0.087	2.581***	5629	-35.297**	4.901***	1.98***
	Recycling	37	0.604	2.83***	0.061***	0.113***	-0.069***	0.009	8.99	-0.005	-41.261***	940	-82.437	5.547***	3.692***
Services	Construction	45	0.386***	0.15***	0.097***	0.175***	-0.106***	-0.022**	0.059***	-0.282***	2.557***	63523	-43.843	5.223***	1.962***
	Automotive	50	0.281***	0.214***	0.123***	0.182***	-0.116***	0	0	0	2.6***	16934	-41.22	4.658***	2.191***
	Wholesale and commission trade	51	0.44***	0.208***	0.121***	0.196***	-0.133***	-0.038*	-0.055**	-0.01	2.343***	76649	-28.854	4.071***	2.038***
	Retail trade	52	0.406***	0.194***	0.125***	0.17***	-0.118***	0	0	0	2.392***	60298	-35.385*	4.686***	2.031***
	Hotels & catering	55	0.298***	0.206***	0.136***	0.164***	-0.115***	0	0	0	2.394***	18132	-29.653	4.662***	1.873***
	Renting of machinery & equipment	71	0.332***	0.4***	0.168***	0.161***	-0.151***	0.112***	0.128**	-0.234	2.006***	7195	-92.397	5.906***	3.197***
	Computer and related activities	72	0.709***	0.022	0.109***	0.226***	-0.15***	0.019	-0.03	0.239*	2.026***	9433	-55.533	5.182***	2.755***
	Other business activities	74	0.484***	-0.028***	0.075***	0.164***	-0.101***	0.01	-0.01	0.098	2.332***	52655	-41.992	4.736***	2.361***
	Legal, technical and advertising	7413	0.701***	0.017	0.084***	0.213***	-0.126***	0.145	0.053	-0.174	2.741***	1690	-49.366	5.311***	2.612***
	Other services	93	0.313***	-0.043	0.127***	0.149***	-0.109***	0	0	0	2.157***	6296	-58.238	5.237***	2.478***

Table A.3: Productivity per type of exporter

		never	always	starter	quitter	switcher
manufacturing	g_{TFP}	0.010 (0.219)	0.002 (0.207)	0.015 (0.218)	-0.001 (0.223)	0.009 (0.223)
	$\epsilon^K + \epsilon^L$	0.929 (0.088)	1.038 (0.110)	0.985 (0.098)	0.980 (0.100)	1.001 (0.095)
	SC	0.000 (0.029)	0.001 (0.024)	0.001 (0.024)	0.002 (0.029)	0.001 (0.023)
	TC^P	0.018 (0.222)	0.003 (0.196)	0.012 (0.215)	0.007 (0.216)	0.011 (0.219)
	TC^K	0.003 (0.056)	0.004 (0.054)	0.003 (0.065)	0.005 (0.069)	0.003 (0.072)
	TC^L	-0.006 (0.062)	-0.005 (0.057)	-0.001 (0.074)	-0.011 (0.076)	-0.005 (0.083)
	TC	0.015 (0.192)	0.002 (0.175)	0.015 (0.193)	0.001 (0.193)	0.009 (0.201)
	EC	-0.005 (0.113)	-0.002 (0.111)	-0.001 (0.106)	-0.004 (0.113)	-0.001 (0.099)
	efficiency	0.831 (0.105)	0.835 (0.098)	0.841 (0.090)	0.834 (0.101)	0.840 (0.087)
	obs	10,685	24,575	5,382	5,126	18,752
services	g_{TFP}	0.019 (0.173)	-0.009 (0.161)	0.046 (0.277)	-0.012 (0.139)	0.014 (0.229)
	$\epsilon^K + \epsilon^L$	0.878 (0.122)	1.013 (0.094)	1.011 (0.108)	0.951 (0.089)	1.003 (0.087)
	SC	0.005 (0.055)	0.004 (0.029)	0.005 (0.035)	0.006 (0.036)	0.003 (0.027)
	TC^P	0.027 (0.151)	-0.011 (0.131)	0.043 (0.276)	-0.003 (0.105)	0.016 (0.222)
	TC^K	-0.005 (0.023)	0.007 (0.019)	0.004 (0.031)	0.001 (0.022)	0.003 (0.031)
	TC^L	-0.002 (0.025)	-0.006 (0.019)	-0.002 (0.029)	-0.007 (0.023)	-0.004 (0.031)
	TC	0.020 (0.130)	-0.010 (0.112)	0.045 (0.252)	-0.009 (0.095)	0.015 (0.205)
	EC	-0.006 (0.099)	-0.002 (0.114)	-0.004 (0.102)	-0.009 (0.101)	-0.004 (0.097)
	efficiency	0.826 (0.097)	0.814 (0.096)	0.809 (0.088)	0.848 (0.094)	0.826 (0.087)
	obs	110,656	6,041	21,546	7,246	27,069

Constructed following Equation (**??**) and Table 1.

Figure A.2: Export discount over time (with matched samples) Note: not cumulative!

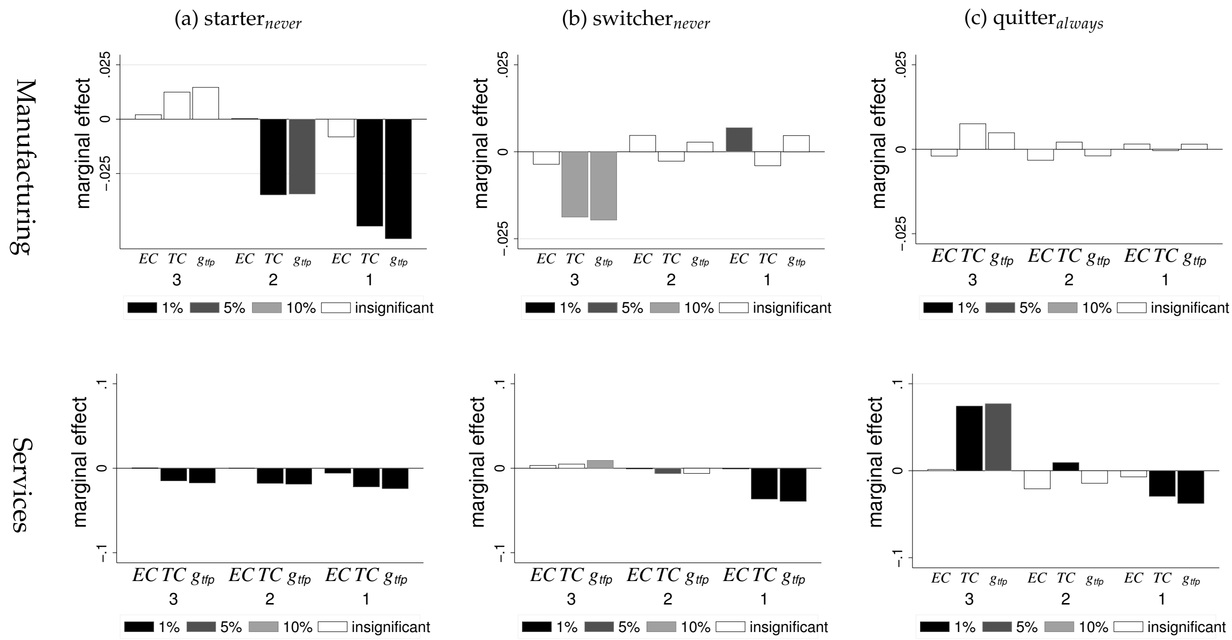

Table A.4: Export Premia in Matched Samples

			g_{TFP}	$\epsilon^K + \epsilon^L$	SC	TC	TC^P	TC^K	TC^L	efficiency	EC
Manufacturing	always$_{never}$	dummy	-0.005*	0.096***	0.001***	-0.011***	-0.012***	-0.001**	0.003***	0.006***	0.005***
	[33,996 | 26]		(0.003)	(0.001)	(0.000)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
		constant	0.009***	0.938***	-0.000	0.0130***	0.015***	0.005***	-0.007***	0.834***	-0.003***
			(0.002)	(0.001)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
		F test	3.695	10581.510	20.406	23.366	23.810	4.470	16.988	28.144	11.619
	starter$_{never}$	dummy	-0.006	-0.046***	-0.000	-0.001	0.003	0.002*	-0.006***	-0.008***	-0.005**
	[15,717 | 27]		(0.004)	(0.001)	(0.000)	(0.003)	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)
		constant	0.016***	0.978***	0.001	0.015***	0.013***	0.001*	0.000	0.840***	0.000
			(0.003)	(0.001)	(0.000)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
		F test	2.377	1008.495	0.814	0.003	0.749	3.163	24.679	22.638	6.390
	quitter$_{always}$	dummy	-0.007**	-0.042***	0.001	-0.004	0.001	0.003***	-0.008***	-0.007***	-0.003**
	[28,900 | 26]		(0.003)	(0.001)	(0.000)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
		constant	0.005***	1.035***	0.001***	0.003**	0.003***	0.004***	-0.004***	0.839***	0.001*
			(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
		F test	4.200	1633.600	2.086	1.847	0.224	8.320	69.783	26.061	4.363
	switcher$_{always}$	dummy	0.005***	-0.029***	0.000	0.007***	0.008***	-0.000	-0.001	0.002**	-0.002*
	[42,375 | 26]		(0.002)	(0.001)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
		constant	0.005***	1.035***	0.001***	0.002*	0.003**	0.004***	-0.004***	0.839***	0.001*
			(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
		F test	6.853	2081.311	0.303	14.467	14.969	0.009	1.467	4.253	2.897
	switcher$_{never}$	dummy	0.004	0.062***	0.001***	-0.001	-0.001	-0.001	0.001	0.008***	0.004***
	[28,937 | 27]		(0.003)	(0.001)	(0.000)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
		constant	0.007***	0.935***	-0.000	0.012***	0.014***	0.004***	-0.006***	0.832***	-0.004***
			(0.002)	(0.001)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
		F test	1.851	3986.053	18.973	0.216	0.131	2.228	1.343	55.076	7.494
Services	always$_{never}$	dummy	-0.025***	0.090***	-0.001**	-0.030***	-0.036***	0.004***	0.003***	0.007***	0.006***
	[45,666 | 6]		(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.002)	(0.002)
		constant	0.010***	0.923***	0.004***	0.012***	0.017***	0.001***	-0.006***	0.812***	-0.006***
			(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
		F test	80.683	3867.966	5.387	223.900	248.303	143.297	38.797	15.855	9.765
	starter$_{never}$	dummy	-0.024***	-0.071***	0.000	-0.021***	-0.017***	-0.001***	-0.004***	-0.011***	-0.003***
	[113,375 | 9]		(0.002)	(0.001)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)
		constant	0.040***	0.972***	0.004***	0.039***	0.040***	-0.004***	0.003***	0.830***	-0.002**
			(0.002)	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)
		F test	152.741	4603.902	0.845	173.150	81.992	9.237	252.080	126.923	10.625
	quitter$_{always}$	dummy	-0.038***	-0.042***	0.001**	-0.031***	-0.016***	-0.007***	-0.008***	-0.013***	-0.009***
	[8,817 | 6]		(0.004)	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.003)
		constant	-0.012***	1.023***	0.002***	-0.017***	-0.022***	0.006***	-0.001	0.824***	0.002
			(0.003)	(0.001)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)	(0.002)	(0.002)
		F test	83.741	489.183	4.991	115.825	23.022	150.714	241.316	25.873	7.987
	switcher$_{always}$	dummy	0.034***	-0.009***	0.001	0.038***	0.040***	-0.003***	0.001***	0.001	-0.005***
	[27,032 | 6]		(0.004)	(0.001)	(0.000)	(0.003)	(0.004)	(0.000)	(0.000)	(0.001)	(0.002)
		constant	-0.021***	1.024***	0.003***	-0.026***	-0.027***	0.006***	-0.004***	0.815***	0.002
			(0.003)	(0.001)	(0.000)	(0.003)	(0.003)	(0.000)	(0.000)	(0.001)	(0.001)
		F test	81.11437	54.36671	1.802293	131.5973	122.9875	44.23964	7.156664	0.437578	9.825604
	switcher$_{never}$	dummy	0.001	0.072***	-0.001**	0.000	-0.002	0.000	0.002***	0.011***	0.002**
	[115,883 | 9]		(0.002)	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)
		constant	0.014***	0.901***	0.004***	0.015***	0.021***	-0.005***	-0.001***	0.821***	-0.005***
			(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
		F test	0.567	5872.797	4.152	0.015	2.110	0.575	94.785	152.714	4.432

Table A.5: The Effect of Export Intensity on Productivity Levels and Growth

			g_{TFP}	$\epsilon^K+\epsilon^L$	SC	TC	TC^P	TC^K	TC^L	efficiency	EC
Manufacturing	always	expint	-0.002	0.017***	0.000	-0.001	-0.001	-0.001	0.000	-0.002**	-0.001
	[24,207 | 26]		(0.002)	(0.001)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
		expint^2	-0.000	-0.002***	-0.000	0.000	0.000	-0.000	0.000	-0.002***	-0.000***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
		constant	0.009***	1.021***	0.001***	0.004*	0.004*	0.005***	-0.005***	0.848***	0.005***
			(0.002)	(0.001)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
		F test	13.758	481.118	0.195	0.3346	0.142	4.072	2.072	551.857	42.892
	starter	expint	-0.016***	0.023***	0.000	-0.017***	-0.018***	-0.004**	0.005***	0.000	0.001
	[5,339 | 27]		(0.006)	(0.002)	(0.001)	(0.005)	(0.006)	(0.002)	(0.002)	(0.002)	(0.003)
		expint^2	0.001	-0.002***	-0.000	0.002*	0.002*	0.001*	-0.001**	-0.002***	-0.001**
			(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
		constant	0.025***	0.974***	0.001	0.023***	0.020***	0.005***	-0.003**	0.845***	0.002
			(0.004)	(0.001)	(0.000)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)	(0.002)
		F test	11.583	93.943	0.175	8.415	7.046	3.633	3.816	36.283	7.952
	quitter	expint	0.021***	0.046***	0.000	0.019***	0.011*	-0.002	0.009***	0.002	0.002
	[5103 | 27]		(0.007)	(0.002)	(0.001)	(0.006)	(0.006)	(0.002)	(0.002)	(0.003)	(0.003)
		expint^2	-0.005***	-0.006***	-0.000	-0.003**	-0.002	0.000	-0.001**	-0.002***	-0.002***
			(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
		constant	-0.004	0.966***	0.002***	-0.004	0.005	0.006***	-0.014***	0.836***	-0.002
			(0.004)	(0.001)	(0.000)	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)
		F test	7.157	214.897	0.683	5.786	1.618	1.255	13.917	19.572	12.859
	switcher	expint	0.003	0.028***	0.001**	0.002	-0.007**	-0.006***	0.015***	-0.002	0.000
	[18679 | 27]		(0.003)	(0.001)	(0.000)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
		expint^2	-0.002***	-0.003***	-0.000*	-0.001	0.000	0.000***	-0.002***	-0.001***	-0.001***
			(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
		constant	0.011***	0.989***	0.001***	0.009***	0.015***	0.006***	-0.012***	0.844***	0.001
			(0.002)	(0.001)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
		F test	13.575	628.636	2.493	1.280	7.739	24.784	117.475	106.255	39.490
Services	always	expint	0.003	0.003**	0.000	0.003	0.003	0.000	-0.001	-0.001	-0.002
	[5645 | 6]		(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.002)	(0.002)
		expint^2	-0.001	-0.000***	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
		constant	-0.003	1.010***	0.004***	-0.011***	-0.012***	0.007***	-0.006***	0.820***	0.004**
			(0.003)	(0.001)	(0.001)	(0.002)	(0.003)	(0.000)	(0.000)	(0.002)	(0.002)
		F test	3.990	4.299	0.322	0.938	0.890	0.008	1.222	2.851	6.225
	starter	expint	0.007**	0.016***	0.001***	0.006**	0.004	-0.001**	0.002***	-0.001	0.000
	[20,652 | 10]		(0.003)	(0.001)	(0.000)	(0.003)	(0.003)	(0.000)	(0.000)	(0.001)	(0.001)
		expint^2	-0.001**	-0.002***	-0.000***	-0.001	-0.000	0.000	-0.000***	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
		constant	0.045***	0.999***	0.005***	0.042***	0.042***	0.004***	-0.004***	0.813***	-0.001
			(0.002)	(0.001)	(0.000)	(0.002)	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)
		F test	3.159	203.817	5.759	3.356	1.653	3.475	34.272	18.328	2.592
	quitter	expint	0.026***	0.045***	0.000	0.021***	0.007	0.012***	0.002*	0.003	0.004
	[7,217 | 10]		(0.006)	(0.004)	(0.002)	(0.004)	(0.004)	(0.001)	(0.001)	(0.004)	(0.004)
		expint^2	-0.003***	-0.004***	-0.000	-0.002***	-0.001*	-0.001***	-0.000	-0.000	-0.000
			(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
		constant	-0.014***	0.946***	0.006***	-0.010***	-0.003**	-0.000	-0.007***	0.849***	-0.009***
			(0.002)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
		F test	11.725	120.216	0.396	15.956	1.792	136.546	5.338	0.321	1.793
	switcher	expint	0.037***	0.019***	0.002***	0.033***	0.021***	0.006***	0.008***	0.000	0.002
	[26672 | 9]		(0.003)	(0.001)	(0.000)	(0.003)	(0.003)	(0.000)	(0.000)	(0.001)	(0.001)
		expint^2	-0.004***	-0.002***	-0.000***	-0.003***	-0.002***	-0.001***	-0.001***	-0.000***	-0.000***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
		constant	0.007***	0.998***	0.003***	0.007***	0.011***	0.002***	-0.006***	0.828***	-0.003***
			(0.002)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
		F test	86.755	218.961	12.412	104.375	37.910	89.927	203.629	25.329	7.602

Figure A.3: Export intensity

(a) g_{tfp} (b) TC (c) EC

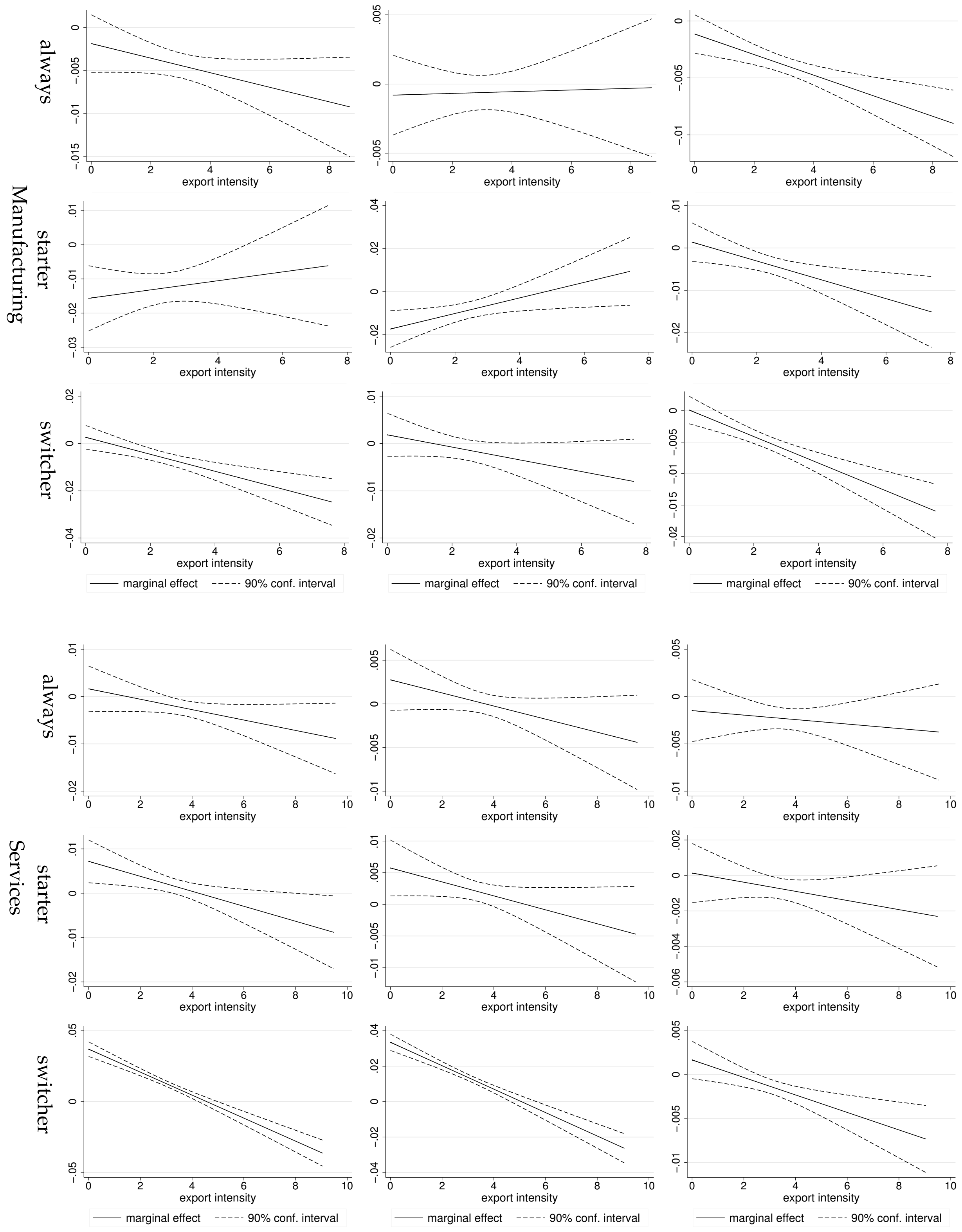

Table A.6: Literature overview

Study	Country	Sample	Methodology	Findings
Aw and Hwang (1995)	Taiwan	2,832 firms; 1986	Translog production function Panel Data	Higher productivity of exporters. Self-selection of exporters. Absence of learning from exporting.
Bernard and Wagner (1997)	Germany	7,624 firms; 1978-92	Panel Data	Higher productivity of exporters. Self-selection of exporters.
Clerides et al. (1998)	Colombia, Mexico, Morrocco	all plants; 1981-91 2,800 firms; 1986-90 all firms; 1984-91	FIML of cost functions Panel Data	Exporters are more efficient than non-exporters. No learning from exporting for Columbian and Mexican firms. Some learning from exporting for Moroccan firms.
Bernard and Jensen (1999)	US	50-60,000 plants; 1984-92	Linear probability with fixed effects	Higher productivity of exporters. Self-selection of exporters. Absence of learning from exporting.
Kraay (1999)	China	2,105 firms; 1988-92	Dynamic Panel	Higher productivity of exporters. Learning from exporting.
Isgut (2001)	Colombia	Large panel of manufacturing firms; 1981-91	Panel Data	Higher productivity of exporters. Evidence supportive of self-selection without ruling out some learning from exporting possibilities.
Castellani (2002)	Italy	2,898 firms; 1989-94	Cross-section	Higher productivity of exporters. Learning associated with export intensity.
Delgado et al. (2002)	Spain	1,766 firms; 1991-96	Non-parametric analysis of productivity distributions.	Higher productivity of exporters. Self-selection of exporters. Inconclusive evidence on learning.
Girma et al. (2004)	UK	8,992; 1988-1999	Matching analysis and difference-in-difference estimators	Higher productivity of exporters. Self-selection of exporters. Exporting may boost productivity.
Bigsten et al. (2004)	Cameron, Ghana, Kenya, Zimbabwe	Panel of manufacturing firms; 1992-95	Simultaneous estimation of production function and export regression GMM and ML estimators	Learning from exporting. Little empirical evidence on self-selection.

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Table A.6 (Continued from previous page)

Study	Country	Sample	Methodology	Findings
Arnold and Hussinger (2004)	Germany	Unbalanced panel data on manufacturing plants;1992-2000	Matching analysis. SP estimator. VAR with fixed effects	Higher productivity of exporters. Self-selection of exporters. Absence of learning from exporting.
Blalock and Gertler (2004)	Indonesia	20,000 plants; 1990-96	Production functions Panel data	Higher productivity of exporters. Learning from exporting. Absence of self-selection of exporters.
Yasar and Rejesus (2005)	Turkey	Unbalanced panel data on manufacturing plants; 1990-96	Propensity score matching analysis and difference-in-difference estimators	Higher productivity of exporters. Learning from exporting.
Van Biesebroeck (2005)	Nine Sub-Saharan African countries	1,800 firms; 1992-96	Production functions. GMM, ML, SP estimators	Higher productivity of exporters. Learning from exporting.
Wagner (2007)	Germany	Unbalanced panel of establishments of mining and manufacturing firms; 2004	Cross section	Higher productivity of exporters, especially for those who export to the non-eurozone countries compared to those who export inside the eurozone. No inference on self-selection vs. learning form exporting.
De Loecker (2007)	Slovenia	7,915 firms; 1994-2000	Matched sampling techniques	Learning from exporting. Higher productivity for exporters who export to high-income regions.