ESSAYS ON FIRM PRODUCTIVITY AND OPENNESS TO FOREIGN TRADE AND INVESTMENT

By Jens Matthias Arnold
Master of Science in Economics, Universitat Pompeu Fabra, Barcelona, 2002
And Diplom-Volkswirt, University of Mannheim, 2001
Matricola 901892

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Thesis Committee:
Gianmarco I. P. Ottaviano
Beata Smarzynska Javorcik
Alessandro Turrini

Università Commerciale Luigi Bocconi
PhD Economics Via Sarfatti 25 20136 Milano Italy

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Chapter 3 tests some of the predictions of recent advances in trade theory that have focused on different trade patterns of firms within the same sector. Helpman, Melitz and Yeaple (2005) develop a model in which innate productivity differences between firms determine the degree of international engagement of firms: The least productive firms produce for the domestic market, better performers engage in export activities, and the top firms establish foreign subsidiaries. Using German firm-level data from 1996 to 2002, the paper tests this prediction using non-parametric methods, by examining the distribution functions of the three subsets of firms for stochastic dominance. Rather than just comparing first moments, this technique allows to compare productivity over the entire distribution. The results show robust support for the prediction from theory.

INTRODUCTION

"Bridging the global productivity divide is essential for fighting poverty and stimulating growth in both output and decent and productive employment", according to the ILO's World Employment Report 2004-05. Productivity is a necessary condition for growth and for creating incomes that allow people to escape from poverty. At the same time, we live in a world in which economies are becoming increasingly open to international trade and investment flows, accompanied by massive changes in the patterns and technologies of production. My thesis is an effort to examine the effects of various aspects of globalization on the productivity of firms in manufacturing industries.

In particular, the present thesis examines productivity with respect to three aspects of openness. Chapter 1 looks at the causal effects of inward foreign direct investment (FDI) in Indonesia on the productivity of acquired firms. The conventional wisdom suggests that multinational companies (MNEs) have an advantage over local firms. But is the superior performance of foreign affiliates due to the intrinsic advantage of a technologically advanced foreign parent company, or are foreign investors simply good at picking the best performing local plants as acquisition targets? The answer to this question is crucial for evaluating the potential for technology spillovers from FDI in a developing country. Applying a matching technique and a difference-in-difference estimator, I am able to separate causality and correlation in the Indonesian firm-level data.

In chapter 2, I examine the dividing line between firms that participate in international trade by exporting into foreign markets and firms that serve only their domestic home market. Given the commonly accepted stylized fact that exporting firms enjoy higher productivity than non-exporters, I examine the direction of causality between these two characteristics. Recent advances of the theoretical literature on international trade identify productivity differences among firms as a determinant for their exporting behavior, but this is a debated issue. A possible alternative hypothesis would be that exporting firms become more productive as they learn from exporting. In each of these two cases, the policy implications would be very different. If there is evidence for learning from exporting, policy makers could subsidize initial exports of particular firms in the hope that learning from exporting will make these exporters self-sustainable after some time. In the opposite case, export promotion policies that try to pick winners rather than giving support to firms in a non-discriminatory way run the risk of wasting public resources. I test the direction of causality for the case of German firms, using a matching technique and the concept of Granger causation.

Finally, chapter 3 extends this analysis by incorporating also firms that establish foreign subsidiaries, and thus engage in outward FDI. The chapter provides evidence of a productivity differential between firms that serve the domestic market only, exporting firms and firms that establish foreign subsidiaries. A recent theoretical contribution shows that there should be a clear productivity rank ordering of firms with respect to the intensity of their foreign engagement (Helpman, Melitz, Yeaple, American Economic Review 2005).

While more productive firms are predicted to be exporters by the model, it will be the highest performers of a given country that become multinational enterprises. The policy implication of this relationship is that it strengthens the case for the potential benefit from FDI, because opening one's doors to FDI implies allowing entry to the best performing firms from other countries. In other words, there is potentially much knowledge that local firms could acquire from the foreign affiliate. I test this pattern using firm-level data from Germany by using the statistical concept of stochastic dominance.

The unifying thread to the three chapters of the present thesis is thus productivity of firms, and its relationship to various aspects of openness. While several studies look at the relationship between these variables at the aggregate level using cross-country regressions, much of the underlying micro-dynamics of these issues, and the policy implications that can be drawn from causal analyses at the micro level, remains undetermined in the empirical literature. My thesis is an attempt to provide answers to some of these questions.

CHAPTER 1

Gifted Kids or Pushy Parents? Foreign Acquisitions and Plant Productivity in Indonesia[1]

1 Introduction

The conventional wisdom suggests that multinational companies have an advantage over local firms, which allows them to offset the extra cost of operating in distant and unfamiliar markets. However, is the superior performance of foreign affiliates due to the intrinsic advantage of a 'pushy' foreign parent company, or are foreign investors simply good at picking the best performing local plants as acquisition targets (the 'gifted kids' in our metaphor)? Recently, the application of sophisticated econometric techniques to longitudinal micro data has cast some doubt on an intuitive positive answer to these questions, often taken for granted by economists and policymakers.[2] As Harris and Robinson (2003) remark, if foreign ownership *per se* is not associated with a productivity advantage, "then it is difficult to see how FDI can have a positive impact on overall (..) productivity and thus growth" in the host country.

This study analyzes the causal link between foreign ownership and plant performance in Indonesia. While to the best of our knowledge this question has not been examined in a developing country context,[3] there are several reasons to expect that the effect of foreign ownership will be particularly pronounced in the developing world. First, the difference in

[1] This paper is joint work with Beata Smarzynska Javorcik. I would like to thank Mona Haddad, Sjamsu Rahardja and Kai Kaiser for making the data available and John Romalis for information on domestic M&As in Indonesia. I am also indebted to Mary Amiti, Ana Fernandes, Aart Kraay, Jan de Loecker, Philippe Martin, Gianmarco Ottaviano, Kathryn Russ, Farid Toubal and seminar participants at the World Bank International Trade Seminar, the Inter-American Development Bank, the European Research Workshop on International Trade, Katholieke Universiteit Leuven, Syracuse University, the Fourth Workshop of the Regional Integration Network in Montevideo sponsored by LACEA, the World Bank-LSE Conference on Industrialization and Development in London and the Empirical Investigations in International Economics conference in Ljubljana for helpful suggestions. Moreover, I thank Edwin Leuven, Sascha Becker and Andrea Ichino for valuable advice on the empirical implementation and Hans Shrader for his support and advice.

[2] Harris and Robinson (2003) demonstrate that foreign investors acquire the best performing firms in the UK, but subsequently the acquired firms do not reap any benefits from foreign ownership. Using Italian data, Benfratello and Sembenelli (2002) provide evidence of a productivity advantage stemming from foreign ownership, but *only* in the case of subsidiaries of US multinationals. Conyon et al. (2002), however, find a 14 percent differential in labor productivity between foreign and domestically owned firms in the UK, which can be attributed to differences in ownership *per se*. Surveying the empirical literature, Barba Navaretti et al. (2004, Chapter 7.3) stress that much of the available empirical evidence "supports a statistical association between foreign ownership and productivity, but not a causal link." They further report that in those studies where a more careful analysis of causality was conducted "differences in productivity between the two groups of firms are smaller than in earlier estimations and often insignificant."

[3] Two notable exception are Djankov and Hoekman (2000) and Evenett and Voicu (2002). Both studies consider only publicly listed companies in the Czech Republic.

technological sophistication between foreign investors and plants they acquire is likely to be larger in developing countries than in industrialized economies. Second, foreign direct investment (FDI) is widely considered to be a key mechanism of cross-border technology transfer.[4] The plausibility of this mechanism is supported by theoretical arguments stressing the importance of intangible assets, transfer of technology from headquarters to foreign affiliates (e.g., Markusen 1995) and the fact that most of the world's R&D effort is undertaken by multinational companies. Additionally, recent theoretical work by Helpman et al. (2004) on heterogenous firms suggests that multinationals come from the upper part of the productivity distribution of firms in their country of origin.[5] Third, the evidence based on stock market data suggests that when firms from developed countries acquire firms in emerging markets, the stock market anticipates significant value creation and substantial gains for shareholders of both acquirer and target firms (Chari et al. 2004).[6]

Disentangling correlation and causality is not straightforward. If high productivity plants are chosen by foreign investors, the ownership status becomes endogenous and a simple least-squares estimation invalid. This is why we use propensity score matching to assess the causal effect of foreign ownership on plant productivity. The matching technique creates the missing counterfactual of an acquired plant had it remained under domestic ownership. It does so by pairing up each plant that will receive FDI in the future with a domestic plant with very similar observable characteristics operating in the same sector and year. Propensity score matching is then combined with a difference-in-differences approach. The causal effect of foreign ownership is hence inferred from the average divergence in the productivity growth paths between each acquired plant and its matched control plant, starting from the pre-acquisition year. This strategy allows us to control for observable and unobservable but constant differences between the acquired and the control plants. While this approach has been widely used in labor economics it has not been applied to the estimation of host country effects of FDI.

Employing this strategy has several advantages. First, unlike studies using the Heckman (1979) two-step procedure, we do not require a variable that influences the probability of receiving FDI but not the subsequent plant performance. Finding a suitable measure is frequently close to impossible. Second, in contrast to the GMM approach, our strategy does not require multiple lags of variables of interest and avoids questions about the appropriateness of lags as instruments. Besides, it is not dependent on the lack of the second-order correlation in the data. Third, it allows us to follow the performance trajectory of FDI recipients rather than just estimating the average effect of receiving FDI. Finally, we are able to trace changes in other aspects of plant operations, such as investment, employment and exporting without having to model them explicitly.

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[4] There is a large literature focusing on knowledge spillovers from FDI. For a review of the literature on *intra-industry* spillovers see Görg and Strobl (2001) and Saggi (2002), for evidence on *inter-industry* spillovers see Javorcik (2004).

[5] This prediction has found empirical support in the context of Germany (Arnold and Hussinger 2005a) and Ireland (Girma, Görg and Strobl 2004).

[6] Gopinath and Romalis (2005) find that such an effect is mainly present during the times of financial crises.

Our analysis, based on the plant-level data from the Census of Indonesian Manufacturing Plants covering the period 1983-96, shows that foreign ownership has a significant positive effect on plant performance measured in terms of total factor productivity (TFP). TFP is estimated at the level of 4-digit sectors using the Levinsohn-Petrin (2003) procedure to correct for simultaneity between productivity shocks and input choices. The estimated increase in plant productivity is quite large, reaching about 34 percent in the third year of foreign ownership. About half of the positive productivity effect is realized during the year foreign investment takes place with the rest occurring during the following two years. While this effect is larger than the 14 percent differential found in the UK by Conyon et al. (2002), it is smaller than the 43 percent advantage obtained for the Czech Republic by Evenett and Voicu (2003). As the productivity gap between domestic plants and multinational companies is most likely considerably larger in a developing country than in the UK, finding a bigger effect in a developing country context is not surprising.

Several robustness checks are performed to assess the validity of the findings. First, we show that the results are robust to extending the time horizon under consideration to five years of foreign ownership. This exercise indicates that receiving FDI leads not only to an immediate boost to productivity but that the improvements continue to take place in subsequent periods. Second, to eliminate the possibility that pre-acquistion trends in productivity may be influencing our findings, we demonstrate that the results hold when matching takes into account the rate of productivity change in the period prior to acquisition. Third, our results are not affected when we relax the restriction of matching within the same sector and year.

Additionally, we provide evidence indicating that productivity improvements take place simultaneously with increases in investment outlays, employment, wages and output, thus suggesting an on-going restructuring process. We also demonstrate that plants receiving foreign investment become more integrated into the global economy by exporting a larger share of their output and sourcing a larger share of their inputs from abroad.

Our results, pointing to profound changes taking place in FDI recipients, are consistent with anecdotal evidence. For instance, when the German company Caatoosee AG acquired an Indonesian software firm, Sigma, the employment in the acquired firm increased by 20 percent within just twelve months.[7] Two years later, AlphaBITS, the software developed by Sigma received Merit Award for the best industrial application at the Asia Pacific ICT Award 2001. It was the first time ever Indonesia participated in the event attended by competitors from 11 countries.[8] Similarly, when H.J. Heinz purchased a majority stake in PT ABC Central Food Industry, maker of Indonesia's hot chili sauce and the world's second largest producer of soy sauce, it did so with an intention to transform the Indonesian plant into a launch pad for an ethnic foods business worldwide.[9] The steel industry provides an example of technology transfer from abroad to an Indonesian subsidiary. The Maspion Stainless Steel Indonesia, a joint venture between Indonesia's PT

[7] http://www.hv-info.de/download/Caatoosee_02-03-31_GB.pdf
[8] http://www.sigma.co.id/history.asp
[9] Source: "U.S. Firms See Hope Amid Woe in Indonesia—A Hardy Few Brave Riots to Make Acquisitions; Ford, Citygroup Wade In" *The Wall Street Journal*, June 1, 1999, A16.

Alumindo and Kanematsu Corp of Japan, is on the way to become the first stainless steel cold rolling mill in Indonesia to produce stainless steel coil and sheet of grades SUS 304 and 43 thanks to the technology provided by Sumitomo Metals of Japan under the technical assistance agreement.[10]

While we have confidence in our results, we also address the plausibility of alternative explanations that could be consistent with the observed pattern. First, we eliminate the possibility that the observed improvements are purely driven by a valuation effect by pointing out that the productivity improvement is not a level effect but a gradual process taking place over a longer period of time. Moreover, as there is no difference between the acquired plants and the control group in terms of royalty payments, our productivity results cannot be attributed exclusively to an introduction of new brand names. We also demonstrate that productivity improvements are present in plants that are not engaged in exporting, importing and do not make royalty payments, which suggests that our findings are not driven by accounting differences related to international transactions motivated by transfer pricing.

Second, to attenuate the concern that the benefit of foreign ownership might be limited to easing credit constraints, our matching procedure includes a binary variable indicating the use of bank loans. Furthermore, our conclusions do not change when matching is performed using a Mahalanobis distance measure that includes the value of investment undertaken *during* the year when foreign investment is received, thus eliminating differences in contemporaneous investment between the treatment and the control group.

Third, our findings are unlikely to be due solely to scale economies. The production functions estimated at the sectoral level indicate that in 77 percent of sectors constant returns to scale cannot be rejected. We also show that foreign ownership is not associated with an increase in capacity utilization. Fourth, we demonstrate that our results cannot be explained by improvements undertaken in preparation for entering foreign markets, as they hold even for the subsample of non-exporting plants.

Fifth, to support our conclusion that it is foreign ownership *per se* rather than mergers and acquisitions in general that leads to an improved performance, we use propensity score matching combined with a difference-in-differences approach to compare productivity outcomes for privatizations into domestic and foreign hands. We show that transfer of public ownership to foreign investors is associated with greater productivity improvements than domestic privatizations. Additionally, we utilize data on several domestic acquisitions from the Securities Data Corporation Mergers and Acquisitions Database to show that in contrast to foreign acquisitions, domestic M&As are not associated with an increase in cost efficiency.

Finally, by confirming our findings using the Generalized Method of Moments (GMM) we eliminate the possibility that our choice of econometric strategy is crucial to our findings.

[10] Source: http://www.alumindo.com/subsidiary.html

To summarize, while there is some indication that better performers become FDI recipients, foreign ownership *per se* is found to lead to an improved performance of acquired plants. Thus we conclude that FDI has a positive direct effect on the productivity of recipient plants in the host country. This finding confirms an implicit assumption made in the literature on FDI spillovers and indicates that FDI indeed presents a potential for knowledge transfer through spillover effects.

The remainder of the paper is structured as follows. The next section reviews the existing literature. Section 3 outlines our empirical strategy for identifying the causal relationship. Section 4 describes the Indonesian Census of Manufacturing. Section 5 provides evidence suggesting that plants receiving FDI exhibit superior performance several years before the change in ownership takes place. Section 6 explains the details of propensity score matching and the difference-in-differences technique used. Section 7 presents the results of this analysis, while Section 8 focuses on robustness checks. The last section concludes.

2 Existing Literature

Multinational companies compensate for disadvantages of operating in foreign and unfamiliar markets through their large endowments of intangible assets, such as, superior technologies, patents, trade secrets, know-how, brand names, management techniques and marketing strategies (Dunning 1993). Indeed the existing empirical literature has shown that firms undertaking FDI are characterized by high levels of R&D relative to sales, a large share of professional and technical workers in total employment, new and/or technically complex products and high levels of product differentiation and advertising (Markusen 1995). It has also been demonstrated that multinational companies tend to invest more in labor training than local firms in host countries.[11] A significant portion of outlays on employee training is associated with technology transfer from the parent company to its foreign subsidiaries. It is not uncommon for staff from headquarters to conduct training in subsidiaries or for subsidiary staff to be trained at headquarters.[12] The combination of large endowment of intangible assets and high investment in staff training suggests that a change from domestic to foreign ownership is likely to lead to improvements in the plant's operations through better production technologies and management techniques.

Performance comparisons between foreign and domestic plants face a number of challenges. Firms acquired by foreign investors are unlikely to be a random sample from the

[11] For instance, according to the survey described by Kertesi and Köllö (2001), foreign-owned firms in Hungary spent 14.2 percent of their investment on training, as compared to 2.4 percent in the case of domestic firms. Similarly, Filer et al. (1995) found that in foreign-owned firms in the Czech Republic spent 4.6 times more than domestic firms on hiring and training. A recent study focusing on Malaysia also showed that foreign-owned firms provide more training to their workers than domestic enterprises (World Bank 1997).

[12] Ramachandaram (1993) shows that as a result of a licensing agreement for technology transfer to a subsidiary, foreign parent companies sent on average 2.46 employees from the headquarters to their fully-owned subsidiaries in India and 1.91 subsidiary employees visited the headquarters for training. For partially-owned foreign projects, the corresponding figures were 0.65 and 0.61.

population. To the extent that the acquisition targets differ systematically from other firms, a problem of simultaneity between ownership status and other performance-relevant variables will arise and bias the estimate of the productivity advantage. Addressing the simultaneity issue imposes strong requirements on the data, as one needs to observe firms changing ownership both before and after the ownership change. Typically, in a short plant-level panel only a handful of such cases can be found.

Therefore, most of the existing literature has focused on documenting the productivity advantage foreign affiliates enjoy over local firm in host countries *without* attempting to assess causality. This literature includes work by Haddad and Harrison (1993) for Morocco, Aitken and Harrison (1999) for Venezuela, Griffith and Simpson (2001) for the UK, Girma et al. (2004) for Ireland and Javorcik (2004) for Lithuania, just to mention a few.

The few studies aiming to examine the *causal* relationship between foreign ownership and firm performance have produced mixed conclusions. Harris and Robinson (2003) and Benfratello and Sembenelli (2002), using data from the UK and Italy, respectively, find that foreigners tend to acquire the best performing local firms and that foreign ownership does not lead to an improved performance of the acquired firm. Conyon (2001) concludes that acquisitions by US multinationals, but not those undertaken by investors from other countries, have a positive effect on the productivity of the acquisition targets in the UK. Girma and Görg (2003), who also consider the UK data, detect a positive effect in the food industry but find no effect in the electronics sector. Only Griffith (1999) who considers the British car industry and Doms and Jensen (1998) focusing on the US find evidence consistent with foreign ownership leading to better performance.

A possible explanation for the lack of consistent findings is that all of the above mentioned studies focused on industrialized countries where the technological gap between multinationals and their acquisition targets is unlikely to be large. One would expect that the positive effect of foreign acquisitions, if it exists, is more likely to manifest itself in developing economies. Yet, with the exception of two studies (Djankov and Hoekman 2000, and Evenett and Voicu 2003) which focused on publicly traded firms in the Czech Republic, this question has not been examined in a developing country context.[13]

Our work aims to fill this gap by focusing on a developing country and applying a methodology that has not been previously used to study this question. We consider ownership changes taking place within a plant, and we aim to address the selection issue by combining propensity score matching with a difference-in-differences estimation. We focus on total factor productivity estimated using the correction for the simultaneity between productivity shocks and input choices, as suggested by Levinsohn and Petrin (2003). In contrast to the earlier studies, we also consider other aspects of a firm's operation and the timing of the changes.

[13] Both studies use the Heckman two-step model to control for the selection of FDI recipients using firm-specific information from the first year available in the sample, which is not necessarily the year preceding FDI inflow. Both conclude that foreign ownership contributes to better performance.

3 Empirical Strategy

The first part of our strategy to address the endogeneity of ownership status is to focus on changes from domestic to foreign ownership taking place *within the same plant*. Naturally, this approach implies a substantial reduction of the number of plants considered. However, a nice feature of our data is that the sample size is large enough that we are still left with a sufficient number of observations to generalize our results with confidence. The advantage of focusing on plants observed before and after an ownership change is that through a difference-in-differences approach we can control for all non-random elements of the acquisition decision that are constant or strongly persistent over time.

Using a difference-in-differences technique allows us to compare the performance of acquired plants with the performance of plants remaining in domestic hands. This comparison, however, is still vulnerable to problems of non-random sample selection. To address the selection issue, we combine a difference-in-differences approach with propensity score matching.[14] The matching procedure controls for the selection bias by restricting the comparison to differences within carefully selected pairs of plants. Each pair consists of an acquired plant and a domestic plant with similar observable characteristics in the year preceding the acquisition of the former.

The aim of the analysis is to estimate the causal effect of foreign ownership on total factor productivity growth, defined as

$$E(Y_1 - Y_0 |_{FDI=1}) = E(Y_1 |_{FDI=1}) - E(Y_0 |_{FDI=1}) \qquad (1)$$

which is the difference between the performance paths of plants that changed ownership (first term) and the analogous outcome of the same plants had they not been acquired by foreign investors (second term).[15] The latter outcome, is, however, an unobserved counterfactual. The matching technique is a way of constructing this missing counterfactual by drawing comparisons conditional on a vector X of observable plant characteristics. The underlying assumption for the validity of the procedure is that conditional on the observable characteristics that are relevant for the acquisition decision, the treated (FDI recipients) and non-treated plants (those remaining in domestic hands) would exhibit a similar performance under the same circumstances:

$$E(Y_1 - Y_0 |_{FDI=1,X}) = \left(E(Y_1 |_{FDI=1,X}) - E(Y_0 |_{FDI=0,X})\right) - \left(E(Y_0 |_{FDI=1,X}) - E(Y_0 |_{FDI=0,X})\right) \qquad (2)$$

[14] Apart from its original applications in labor economics, the matching estimator has become increasingly popular in causal analyses in other areas of economics. Girma et al. (2004) and Arnold and Hussinger (2005b) apply this technique to examine the relationship between firm productivity and exporting. Barba Navaretti and Castellani (2004) also use this technique to examine the impact of outward FDI on home performance for a sample of Italian firms.

[15] Our notation is to be read as follows: The outcome variable Y represents productivity growth across the ownership change of the acquired (treatment) plants. Its subscript describes the (potentially hypothetical) circumstances under which an outcome is observed, while FDI=1 indicates reference to the group of firms that have been acquired in reality, i.e. our treatment group. Similarly, FDI=0 refers to control observations.

The second difference in equation 2 is the selection bias, which is assumed to be zero conditional on X. It represents the difference between the outcome of the acquired plants, under the hypothetical circumstances that they had they not been acquired, and those plants that remained in domestic hands, in the same (and this time true) situation of no ownership change. If the selection bias represented by the second term is zero for given realizations of the vector X, then we are left with only the causal effect. In other words, the performance difference between acquired plants and the carefully selected group of control observations is a consistent estimate of the causal effect under the matching assumption. Hence, if our matching process is successful, we can give a causal interpretation to the average performance difference between treatment and control plants.

Conditioning on a vector of variables is difficult, since it requires weighting differences in one dimension against another. Rosenbaum and Rubin (1983) provide a proof that conditioning on the propensity score is equivalent to conditioning on all variables in the treatment model. The propensity score is the predicted probability of treatment, which in our case is the probability of a plant receiving FDI. Making use of this result, we employ propensity score matching and compare the performance of plants within the pairs of observations matched on the propensity score. We also make sure that the matched control observations are assigned only from the same year and the same sector as the acquired plant. This eliminates the possibility that productivity differences across sector/year combinations exert influence on our estimated effects and shifts the focus of attention to the position of each plant with respect to the performance of others in the same sector and year.

The combination of matching and a difference-in-differences approach means that we look for divergence in the paths of performance between the acquired plants and the matched control plants that had similar characteristics in the pre-acquisition year. The performance analysis begins in the pre-acquisition period and focuses on the (cumulative) change in performance over the following year and then each of the subsequent two periods. Blundell and Costa Dias (2000) emphasize the benefits of combining matching and a difference-in-differences approach for controlling for observable and unobservable but constant differences between treatment and control units. While matching accounts for differences in observable characteristics, its combination with difference-in-differences analysis provides "scope for an unobserved determinant of participation as long as it can be represented by separable individual- and/or time-specific components of the error term." Examples of such determinants include a particular plant being chosen as an acquisition target because of the qualities of its manager or a foreign investor's preference for a plant possessing particular tangible assets (e.g., a distribution network) or intangible assets (an established brand name).

As the performance measure, we employ total factor productivity, defined as the residual of a Cobb-Douglas production function. We address the simultaneity problem in input choices by applying a semi-parametric estimator proposed by Levinsohn and Petrin (2003) with intermediate input use serving as a proxy for productivity shocks. More specifically, we utilize information the amount of electricity consumed by each plant. As electricity cannot be stored, its consumption is likely to follow changes in production activity more closely than the use of materials.

4 Data

Indonesia is a suitable choice for studying the effects of FDI. The country's industrial success is a relatively recent phenomenon, and there have been significant inflows of foreign direct investment in the last two decades. In terms of GDP, the importance of foreign direct investment inflows has been rising steadily and significantly from the mid-1980s onwards, as can be seen from Figure A1. For the period 1990-1996, the country was the fifth largest developing country recipient of FDI (IFC 1997, p.17).

Historically, the Indonesian manufacturing sector (excluding oil-related activities) has been of almost negligible importance until the 1970s, accounting for less than 10 percent of GDP in 1974-76. Only in the 1980s did the country begin to emerge as a significant industrial power. The attitude towards foreign direct investment has been generally welcoming since the late 1960s.

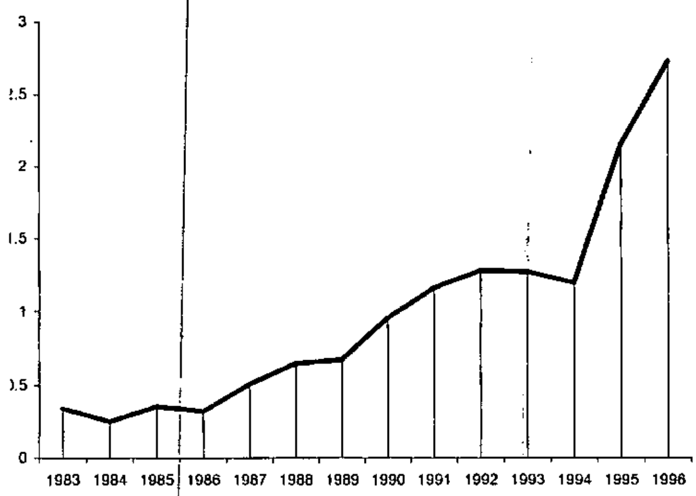
However, as economic policy began to reduce trade barriers and deregulate industry in the early 1980s, Indonesia received a new surge in FDI inflows that tended to be geared towards efficient and internationally competitive activities, mainly in the manufacturing sector (Hill, 2000, p.76). This coincides with the beginning of our data window.

The data used in this paper come from the "Survei Manufaktur," the Indonesian Census of Manufacturing, which has been conducted by the National Statistical Office (BPS) on annual basis since 1975. The census surveys all registered manufacturing plants with more than 20 employees.[16] It contains detailed information on a large number of variables pertaining to input and output flows. There is some variation on the availability of variables from year to year, and the information of interest to us is available from as early as 1983. As the last year of our sample, we include 1996 in order to avoid capturing the effects of the Asian financial crisis, which strongly affected Indonesia beginning in 1997. In particular, we are concerned about a decline in the data quality due to the crisis and about a change in the motivation for foreign acquisitions in times when many Indonesian plants found themselves in financial distress. Our sample, covering the period 1983 -1996, contains more than 210 000 plant observations, of which about 5 percent belong to foreign-owned plants. The average spell a plant remains in our sample is between 8 and 9 years.[17]

[16] Since regional statistical offices in Indonesia have financial incentives to obtain the relevant information from all active firms, we can be reasonably confident that the entire manufacturing sector above the 20 employee threshold is included in our sample. The survey questionnaires can be accessed online at http://www.rand.org/labor/bps.data/webdocs/statistik_industri/si_main.htm.

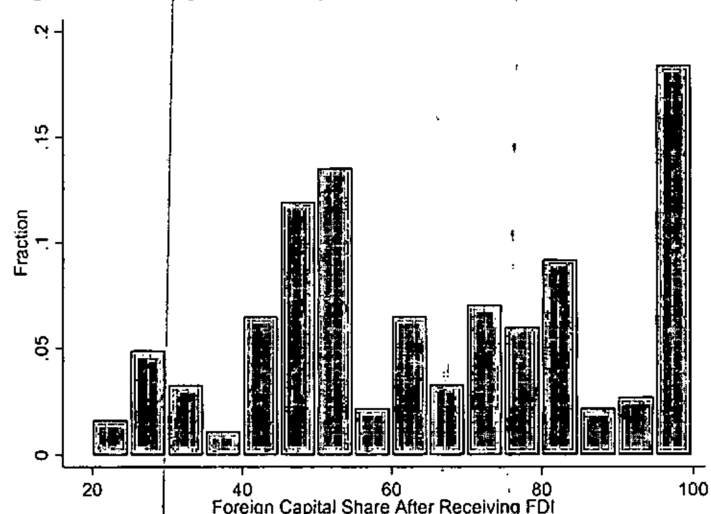
[17] The data have been cleaned conservatively for obvious keypunch errors. Particularly for the share of foreign ownership, we replaced outlier values with adjacent values whenever there was a drop to zero followed by a return to the previous value (e.g. 58, 58, 0, 58), or a different position of the decimal point followed by a return to the previous value (as in 60, 6, 60, 60) .

Figure A1. Net FDI Inflows to Indonesia, as a % of GDP



Source: World Bank Development Indicators

Figure A2. Foreign Ownership Share after Acquisition



In order to estimate the production function, we make use of the information on output (net of energy costs) and four factors of production: the number of production and non-production workers, materials and capital. The capital stock variable has been newly constructed using the perpetual inventory method, making use of detailed data on investment in land, buildings, machinery, vehicles and other fixed assets.[18] To each investment data series (land, buildings, etc.) we applied estimated depreciation rates from Harris et al. (1994).[19]

Since the data contain no information on physical quantities of inputs used or output produced by plants, we are forced to start with nominal values instead. These are deflated using a set of 192 wholesale price indices for manufactured commodities, published by the Indonesian Statistical Office. The commodity indices are mapped to the 5-digit ISIC classification using a concordance table provided by the Statistical Office. These detailed 5-digit ISIC level deflators are applied to plant output and material inputs. Figures on investment and capital are deflated as follows. For buildings, we use a wholesale price index for residential and commercial buildings (WPI) published in the Statistical Yearbook of Indonesia, and for machinery and vehicles the average of the WPIs for 5-digit sectors producing machinery and vehicles, respectively. For other assets, we employ the economy-wide WPI. Unfortunately, the Indonesian Statistical Office does not publish a wholesale price index for energy, so we were constrained to use a CPI specific to energy instead.

The production function is assumed to be Cobb-Douglas and is estimated using the semiparametric procedure suggested by Levinsohn and Petrin (2003).[20] As a proxy for unobserved productivity shocks that may influence the input decision of the plant, we employ the amount of electricity consumed by each plant. The data contain information on electricity consumption net of own production and sales to other plants, expressed in physical quantities (kWh) which rules out measurement errors related to deflation. Our productivity measure is the residual of the production function in logarithmic form. We allow the coefficient estimates to differ over 62 manufacturing sectors, which is equivalent to the 4-digit ISIC level.[21] Given a substantial number of missing values in our data set, we

[18] We used the earliest available information on self-reported replacement values of each capital category as an anchor for the perpetual inventory method. Where a plant did not report the replacement values of its assets, we used the self-reported book values instead. Plants that never report capital stocks were dropped from our sample. Since the investment question was not asked in 1996, for that year we used linear extrapolation on the basis of real investment figures reported for the earlier years

[19] The assumed annual depreciation rate for buildings is 3.3 percent, for machinery 10 percent, and for vehicles and other fixed assets 20 percent. For land, we assumed no depreciation. These rates are very similar to estimates presented in Goeltom (1995).

[20] The estimation was implemented in Stata 8 using the program described in Levinsohn et al. (2003). In 29 out of 62 industries this procedure moved the coefficient on capital in the expected upward direction when compared to a fixed effects estimation of the production function. This makes us feel confident that the correction is performing sufficiently well.

[21] The industry breakdown was adjusted to eliminate inconsistencies caused by the fact that BPS had removed several sectors and introduced a few others into the classification during the period of interest. In such cases, plants were regrouped into the corresponding ISIC Rev. 2 industries. Two petroleum sectors (ISIC 3530 and 3540) were dropped from the sample because of a very small

are able to estimate TFP for about 120,000 plant observations. To avoid capturing effects caused by a change in principal activity of the plant, our matching analysis focuses only on plants that do not switch their sector of operation.[22]

We perform our analysis on 185 plants that switched from domestic to foreign ownership and remain in the data sufficiently long to be observed in the year before the acquisition, the acquisition period and two subsequent years.[23] This is a considerable number, considering that Conyon et al. (2000) find only 129 cases of foreign acquisitions with enough non-missing data to make them suitable for their analysis. Their study analyzes a large developed country (the UK) and covers almost the same time period (1987-96). In a UK data set covering the period from 1980 to 1994, Girma and Görg (2003) are able to identify only 266 foreign acquisitions. Figures A3 and A4 show the distribution of acquired plants in our data across years and sectors, respectively. Ownership changes occur in each 2-digit sector and in each year during the 1984-94 period.[24]

number of observations. ISIC sectors 3901-3909 (Manufacturing industries not elsewhere classified) were also dropped due to concerns about plant heterogeneity within these sectors.

[22] Recall the we assign matches within the same sector and year to assure comparability. Considering plants that switch from one sector to another would make it impossible to maintain this matching restriction.

[23] We consider all plants with a foreign capital share above 20 percent as foreign owned. In practice, however, the exact value of this threshold does not matter because in more than 95 percent of acquisition cases the foreign capital share increased from 0 to 25 or more percent. Figure A2 depicts the distribution of foreign ownership share in the year following the entry of a foreign investor.

[24] Note that we do not consider changes in ownership taking place after 1994 as we want to observe each plant for at least two years after such a change has taken place.

Fire A3. Distribution of Foreign Acquisitions by Year

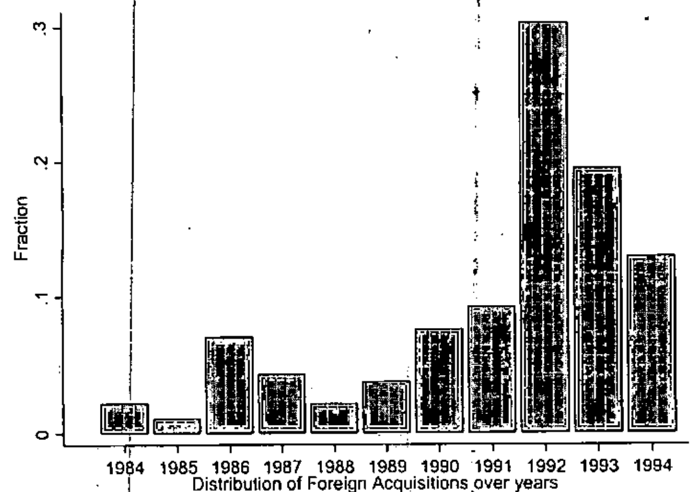
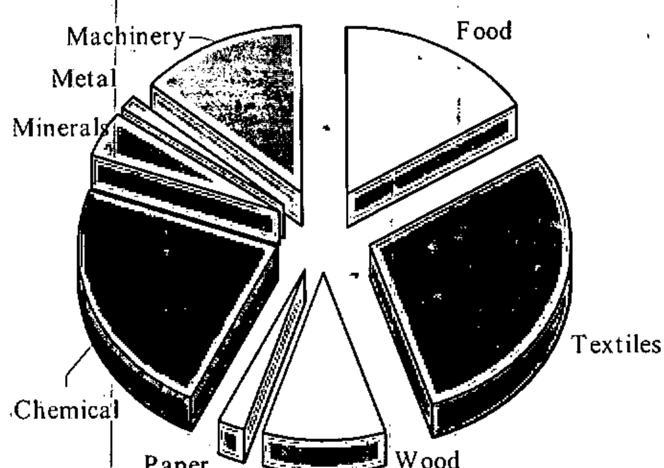


Figure A4. Distribution of Foreign Acquisitions by Sector



5 Evidence of the Selection Bias

Our empirical strategy is driven by our concern about the selection bias that may result from better performing plants being acquired by foreign investors. To examine whether this concern is justified, we regress total factor productivity on a dummy for plants with foreign ownership in year t and a dummy for future acquisition targets during the three years prior to the ownership change.[25] The model also includes industry, region and year fixed effects. We exclude plants with foreign ownership throughout the period.

The estimation results, presented in Table 1, demonstrate that future acquisition targets of foreign investors outperform other Indonesian plants during the three years preceding the ownership change. Not surprisingly, we also find that plants with foreign ownership exhibit a higher productivity than domestic plants. The magnitude of the effect is equal to 19.5 percent for future acquisition targets and 39 percent for plants with foreign ownership.

We interpret this finding as indicating that foreign investors acquire domestic plants with an above average performance, a pattern sometimes called "cherry picking" in the literature. The evidence is strong enough to make a strategy of simply ignoring the issue imprudent. Therefore, in our analysis of the causal effect of foreign ownership on the plant performance, we will control for the selection bias. At the same time, the productivity premium exhibited by plants under foreign ownership is twice as large as the premium exhibited before receiving FDI, suggesting that foreign ownership may also have a positive effect on plant performance. In the next section, we analyze this relationship in more detail.

Table 1. Evidence of the Selection Bias

Dependent Variable is Log TFP	Premium
Plant will receive FDI within next 3 years	0.178***
	(0.022)
Foreign Ownership	0.331***
	(0.009)
No. of observations	111,707

The regression includes industry, year and region fixed effects.
Plants under foreign ownership throughout the period are excluded from the sample.
*, **, *** indicate statistical significance at the 10, 5 and 1% level, respectively.

Controlling for the Sample Selection using the Matching Technique

In order to make a meaningful comparison between the performance of Indonesian plants acquired by foreign investors and those remaining in domestic hands, we need to create a missing counterfactual capturing the performance of the acquired plants had they not received FDI. We do so by applying propensity score matching to identify a suitable plant under continued domestic ownership to which we can compare each acquired plant. The

[25] For example, in the case of a firm that receives FDI in 1993, the dummy would take on the value of one for 1990, 1991 and 1992 and zero for all other years.

requirement for a suitable control observation is sufficient similarity to the future acquisition target with respect to key determinants of the acquisition decision, so as to make these two plants *a priori* equally probable targets of a potential foreign acquisition.

For obvious reasons, the control group is created on basis of observable plant characteristics. We believe that this is a good starting point as potential foreign investors rely heavily on basic observable characteristics of plants, such as their age, size, employment composition, machinery and equipment available, productivity, etc. to narrow down the number of potential acquisition targets. They may also judge suitability of plants based on their reliance on imported inputs which may indicate the sophistication level of the technology used. Finally, the fact that an establishment has received a bank loan may also contain information on financial institutions' perceptions about trustworthiness and future prospects of an establishment. All of these factors are taken into account when constructing the control group.

We use one-to-one nearest neighbor matching on the propensity score, which expresses the estimated probability of a plant becoming acquired by a foreign investor.[26] As mentioned in Section 3, this solves the dimensionality problem when considering differences on more than one observable characteristic. Moreover, we impose the additional requirement that the matched plant observations come from the same sector and year.[27] Therefore, in a first step, we use a probit regression to model the binary outcome of a plant becoming acquired by foreigners on the basis of plant-specific characteristics. To avoid endogeneity, all explanatory variables (except for age) are lagged one year.[28]

The results from the probit regression, presented in Table 2, indicate that plants acquired by foreign investors differ systematically from other domestic plants. The model suggests that younger and larger (in terms of employment) plants are more likely to become acquired. The model allows for nonlinear effects of these two variables which indeed appear to be statistically significant. Further, the data show that plants with higher capital-labor ratio, plants engaged in sourcing inputs from abroad and plants with a higher fraction of white-collar employees tend to be more attractive to foreign investors. As the goal of the study is to examine improvements in productivity due to the change in ownership, the model includes controls for the TFP level (normalized by the average TFP observed in the same industry and year) in the period prior to receiving FDI. This variable does not appear to be statistically significant, which is most likely due to a high correlation with other controls. Recall, however, that the results presented in the previous section suggest that the acquired plants exhibit superior performance already three years before the acquisition.

[26] We also tried other matching methods, such as kernel matching and caliper matching, and the results were qualitatively similar.
[27] Our matching procedure is implemented in Stata 8 using a modified version of the procedure described in Leuven and Sianesi (2001). The modifications were necessary to make sure that matched pairs come from the same year and sector.
[28] In order to increase the precision of our model, we dropped all combinations of sectors, years and regions where no foreign acquisitions occurred. Not making this adjustment would increase the number of observations in Table 2 to 57,607 but would not change the conclusions of the paper.

To eliminate the possibility that improvements observed after the ownership change may be due to investments undertaken by plants prior to or in preparation for a foreign acquisition, the matching procedure controls for investment outlays lagged one period. This variable, however, does not appear to be statistically significant. To attenuate the possibility that the effect of FDI works purely through easing access to credit, the probit model also includes a dummy for plants having a bank loan but again the coefficient does not reach conventional significance levels. Finally, the model includes a dummy for plants with public ownership and a time trend, neither of which are statistically significant.

To assess how well the propensity score matching performs in our case, we calculate the difference between the treated and the control group in terms of each of the above variables and run simple t-tests on the differences within 8 bands of the propensity score. This test is called the balancing hypothesis, and it can be performed using the procedure suggested by Becker and Ichino (2002). All of the differences are found to be small and statistically insignificant. This gives us confidence that our approach is capable of grouping together relatively homogeneous plants.[29]

The predicted probabilities are used to assign to each future acquisition target a domestic plant that has the closest propensity score within the same year and sector. Thanks to a large number of available control observations in our data, the matching procedure produces an average distance in propensity scores within matched pairs of less than 4 percent, with a standard variation of approximately 5 percent. This convinces us that our matching procedure has managed to find appropriate comparison observations for each acquired plant.

[29] In our matching procedure we also exclude observations outside the common support. The common support is bound by the lowest propensity score of a treatment observation and the highest propensity score of a control observation.

Table 2. Probit results

Dependent Variable: Foreign acquisition

ln Employment	0.813***
	(0.246)
ln Employment^2	-0.069***
	(0.023)
Age	-0.051***
	(0.008)
Age^2	0.0006***
	(0.0001)
ln Capital intensity	0.084***
	(0.201)
Share of imported inputs	0.650***
	(0.102)
Ratio of non-production workers	1.170***
	(0.243)
ln Relative TFP	0.059
	(0.076)
ln Investment	-0.003
	(0.010)
Bank loan dummy	0.0003
	(0.0003)
Public ownership dummy	0.110
	(0.157)
Time trend	0.026
	(0.016)
Intercept	-4.042***
	(0.645)
No. of obs.	2,355
Chi^2	186.01
Prob > Chi^2	0.00
Pseudo R^2	0.11

All explanatory variables with the exception of age and age^2 are lagged one year. *, **, *** indicate statistical significance at the 10, 5 and 1% level, respectively

6 Results from the Difference-in-Differences Analysis on the Matched Sample

(a) Baseline results

The primary result of interest is the average difference in TFP in the matched pairs, net of the average initial difference before the acquisition. As can be seen in Table 3, between the year prior to the acquisition, in which the matches are assigned, and the acquisition year, the treatment and control observations diverge significantly in terms of productivity. A foreign acquisition leads to an additional 15-percent productivity boost in the acquired plants, which is not shared by similar plants remaining in domestic hands. In the subsequent years, the divergence in performance becomes even greater. By the end of the third year of foreign ownership, the acquired plants enjoy a 34-percent productivity advantage over the control group. The results are significant at the five percent level in the acquisition year and at the one percent level in the following two years.

Table 3. Matching Results for Productivity

Effect of Foreign Acquisition	Log TFP
Acquisition year[(a)]	0.147**
	(0.065)
One year later[(b)]	0.259***
	(0.068)
Two years later[(c)]	0.293***
	(0.074)
N	185

Average Treatment Effect on the Treated (ATT), bootstrapped standard errors in parentheses.
n = number of matched acquisitions
*, **, *** indicate statistical significance at the 10, 5 and 1% level, respectively.

$$\text{(a) ATT} = \frac{1}{n}\sum_{1}^{n}\left(\ln TFP^{treated}_{acquisition\ year} - \ln TFP^{control}_{acquisition\ year}\right) - \frac{1}{n}\sum_{1}^{n}\left(\ln TFP^{treated}_{pre\text{-}acquisition\ year} - \ln TFP^{control}_{pre\text{-}acquisition\ year}\right)$$

$$\text{(b) ATT} = \frac{1}{n}\sum_{1}^{n}\left(\ln TFP^{treated}_{acquisition\ year+1} - \ln TFP^{control}_{acquisition\ year+1}\right) - \frac{1}{n}\sum_{1}^{n}\left(\ln TFP^{treated}_{pre\text{-}acquisition\ year} - \ln TFP^{control}_{pre\text{-}acquisition\ year}\right)$$

$$\text{(c) ATT} = \frac{1}{n}\sum_{1}^{n}\left(\ln TFP^{treated}_{acquisition\ year+2} - \ln TFP^{control}_{acquisition\ year+2}\right) - \frac{1}{n}\sum_{1}^{n}\left(\ln TFP^{treated}_{pre\text{-}acquisition\ year} - \ln TFP^{control}_{pre\text{-}acquisition\ year}\right)$$

These figures are quite compelling. Performance improvements resulting from foreign acquisitions are likely to be larger in developing countries where the productivity gap between domestic plants and multinational companies is considerably greater. Thus, our result of a 34 percentage-point productivity advantage over a three-year horizon seems plausible when compared to the 14 percent improvement found by Conyon et al. (2002) in the UK. It is also smaller than the 43 percent improvement found by Evenett and Voicu (2003) in the Czech Republic.

(b) Extending the time horizon

To confirm that the observed productivity improvement is not a temporary phenomenon, we extend the time horizon to cover two more years after the acquisition. The difference-in-differences results presented in Table 4 indicate that improvements experienced by acquired plants as a result of a foreign acquisition continue in the third and fourth year after the acquisition. By the end of the fourth year, the productivity gap between the acquired and the control plants widens to 40 percentage points. As extending the time horizon limits the size of the sample, in the remainder of the study we will focus on the time horizon considered originally.

Table 4. Matching Results - Longer Horizon

Effect of Foreign Acquisition	Log TFP	Log TFP
Acquisition year	0.152**	0.098
	(0.07)	(0.09)
One year later	0.275**	0.202**
	(0.08)	(0.08)
Two years later	0.316***	0.248**
	(0.11)	(0.11)
Three years later	0.382***	0.354***
	(0.11)	(0.11)
Four years later		0.327***
		(0.11)
N	152	108

Average Treatment Effect on the Treated. Bootstrapped std errors in parentheses.
*, **, *** indicate statistical significance at the 10, 5 and 1% level, respectively.

It is worth pointing out that the observed effects of foreign ownership are driven by an improved performance of the acquired plants rather than by a deterioration in the situation of the control group. If we were to compare to the acquired plants to the *average* performer in the same sector and year (rather than to the control group), the advantage of foreign ownership would appear to be even greater. This suggests that the propensity score matching performs well in constructing a suitable control group.

(c) Removing the restriction on matching within sectors
To ensure that our matching results are not distorted by restricting the control observations to come from the same sector and the same time period, below we present the results obtained without imposing this constraint. As evident from Table 5, this modification leads to the same qualitative conclusions. Allowing out-of-sector matching, however, produces somewhat smaller effects. The estimated productivity advantage is almost identical regardless of whether the absolute TFP measure or the TFP relative to the industry average in a given year is considered.[30]

Table 5. Matching Results for Productivity, not restricted within sector/year

Effect of Foreign Acquisition	Relative TFP	Log TFP
Acquisition year	0.134**	0.132**
	(0.06)	(0.06)
One year later	0.225***	0.221***
	(0.06)	(0.06)
Two years later	0.208***	0.215***
	(0.07)	(0.06)
n	213	213

Average Treatment Effect on the Treated. Bootstrapped std errors in parentheses.
*, **, *** indicate statistical significance at the 10, 5 and 1% level, respectively.

[30] Note that in this case it makes sense to consider both absolute and relative TFP measures because sectoral averages do not cancel out as the treated and the control observations may belong to different sectors.

(d) Accounting for productivity trends prior to acquisition

The difference-in-differences approach removes plant-specific time-invariant effects, however, unobservable but not time-invariant plant-specific characteristics still may pose a main challenge in the analysis. While in some subfields of development economics this issue is addressed by the use of randomized experiments, this is unfortunately not an option in our context.

As a step toward addressing this issue, we account for pre-acquisition trends in plant performance in the matching stage. We construct a new control group based on a new propensity score including the *productivity change in the period preceding the acquisition* in addition to the *productivity level* and all other variables used in Table 2.[31] This requires one additional observation per plant and thus reduces the sample size. The difference-in-differences approach applied to the newly created matched sample produces no statistically significant divergence between the treated and the control group in the year when FDI is received. A statistically significant difference is found, however, in the first and the second year following the acquisition (see Table 6). Thus this robustness check supports our conclusion that FDI recipients outperform plants remaining in domestic hands.

The effects found in Table 6 are smaller than those obtained earlier, amounting to a 22-percent difference within three years as opposed to a 34-percent divergence. The difference in magnitudes, however, appears to be driven by the fact that for many acquired plants we do not observe productivity two years before the acquisition and are thus unable to include them in this robustness check. When we reproduce the results of Table 3 restricting the sample to the 99 plants for which such information is available (see column 2 in Table 6), the estimated effects closely resemble those presented in the first column of Table 6.

Table 6. Sample Matched on Lagged TFP Growth

Effect of Foreign Acquisition	Log TFP (matched on lagged TFP growth)	Log TFP (matching corresponding to Table 3)
Acquisition year	0.034	0.035
	(0.08)	(0.07)
One year later	0.185**	0.168*
	(0.08)	(0.09)
Two years later	0.201**	0.181*
	(0.10)	(0.09)
N	99	99

Average Treatment Effect on the Treated. Bootstrapped std errors in parentheses. *, **, *** indicate statistical significance at the 10, 5 and 1% level, respectively.

(e) Evidence of restructuring

[31] The productivity change is calculated as the first difference of log TFP in the pre-acquisition period while the level refers to the log of TFP relative to the sector/year average in that same year. The latter normalization is done in order to assure comparability (recall that TFP estimates come from regressions performed at the sectoral level). Neither the productivity change nor the productivity level, however, appear to be statistically significant in the probit model.

If our findings of improved productivity are due to FDI, we would expect to observe foreign owners introduce other changes to plant operations. Indeed we find evidence that acquired plants undergo a restructuring process. As illustrated in Table 7, acquired plants grow much faster between the pre- and the post-acquisition period than the control establishments, implying that foreign ownership helps them increase their output and employment. Further, the acquired plants increase employee wages faster than the control group.[32] In addition, plants receiving FDI see a larger rise in their investment outlays relative to establishments remaining in domestic hands. All of the mentioned effects are statistically significant throughout the period considered. They are also consistent with the anecdotal evidence mentioned in the introduction.

Table 7. Matching Results for Output, Employment, Wages, Investment

Effect of Foreign Acquisition	Log Output	Log Employment	Log Wages	Log Investment
Acquisition year	0.665***	0.318***	0.397***	1.561***
	(0.14)	(0.08)	(0.09)	(0.52)
One year later	0.781***	0.311***	0.382***	1.509**
	(0.16)	(0.08)	(0.10)	(0.64)
Two years later	0.826***	0.331**	0.407***	1.069*
	(0.16)	(0.10)	(0.10)	(0.64)
n	185	185	185	185

Average Treatment Effect on the Treated. Bootstrapped std errors in parentheses.
*, **, *** indicate statistical significance at the 10, 5 and 1% level, respectively.

The results also indicate that foreign ownership affects participation of the acquired plants in international markets. As illustrated in Table 8, a foreign acquisition leads to an increase the share of output exported by 11 percentage points in the year of acquisition and by an additional 3 percentage points in the following year.[33] A similar pattern is observed with respect to the reliance on imported inputs. In the acquisition year, treated plants increase the share of imported inputs by 8 percentage points more than the control group. Two years later this difference increases to 12.7 percentage points. Increased reliance on imported intermediates and the ability to enter or expand the presence in foreign markets also suggest that profound changes to the production process may be taking place in the acquired plants.

[32] This is to be expected as the existing literature has documented that foreign establishments tend to pay higher wages than domestic plants. See Sjoholm and Lipsey (2003 and 2004) for a careful analysis of the Indonesian case.

[33] This increase in the average export share is a result of both increased export intensity of previously exporting plants and of plants entering foreign markets for the first time after the acquisition. The reduction in the sample size is due to the unavailability of information on exports in the Census data before 1990.

Table 8. Matching Results for Export Ratio and Ratio of Imported Inputs

Effect of Foreign Acquisition	Exports/Sales	Imported Inputs/Inputs
Acquisition year	11.43**	8.32*
	(5.07)	(3.37)
One year later	14.20**	10.25**
	(5.67)	(4.02)
Two years later	14.26**	12.71***
	(5.88)	(3.92)
n	133	185

Average Treatment Effect on the Treated. Bootstrapped std errors in parentheses.
*, **, *** indicate statistical significance at the 10, 5 and 1% level, respectively.

To sum up, we observe significant changes in the way that plants are managed once they receive FDI. The foreign acquisition seems to unleash an acquired plant's growth potential both in terms of productivity and size. The improvements materialize quickly and continue over time. Acquisitions also raise investment and wages and intensify the plants' participation in the global economy.

7 Addressing Alternative Explanations

As argued earlier, the fact that multinational corporations are characterized by large endowments of intangible assets, high productivity and a willingness to invest in staff training suggests that the observed productivity improvements associated with foreign acquisitions are likely to result from the introduction of new technologies and management techniques and restructuring of plant operations. There exist, however, other explanations which could potentially be consistent with the observed productivity improvements. In this section we explore their plausibility.

(a) Can the results be explained by valuation?
A valuation effect stemming, for instance, from a change in accounting procedures or from an introduction of a brand name, is not a likely explanation for the observed patterns. First, such an effect would lead to a one-time jump in the observed productivity. This is clearly not the case in our sample as we observe a sustained productivity growth over a three-year period. Second, a mere valuation effect would not explain changes in other aspects of plant operations, such as employment, participation in the global economy and so on. Third, it is difficult to argue that our findings are purely due to the introduction of a parent company's brand name without any changes being made to the products to which the trademark is then applied. In most cases, the fear of a brand-name erosion would make foreign owners hesitant to apply their trademark to a product unless they are absolutely sure that the company-wide quality standards have been met. Further, royalty payments for the use of the parent company's brand name would be reflected in the company's accounts. Yet, the results from the difference-in-differences approach suggest that the acquired plants do not diverge from the control group in terms of royalty payments made (see Table 9).

Table 9. Matching Results for Royalty Payments

Effect of Foreign Acquisition	Royalty Payments
Acquisition year	0.308
	(0.58)
One year later	1.286*
	(0.71)
Two years later	1.195
	(0.74)
n	60

Average Treatment Effect on the Treated. Bootstrapped std errors in parentheses. *, **, *** indicate statistical significance at the 10, 5 and 1% level, respectively.

Fourth, while transfer pricing could potentially influence our findings, we believe that this is an unlikely explanation. Accounting statements in Indonesia are prepared according to well-established accounting standards, which are directly based on the U.S. Generally Accepted Accounting Principles (GAAP) (Asian Development Bank 2003, p.97). This suggests that the quality of accounting is reasonably high, particularly in a developing country context. The degree to which transfer pricing motives can introduce measurement errors is limited by these accounting standards. In any event, the incentives for transfer pricing are probably small, because corporate taxes in Indonesia are not much different from those in OECD countries.[34] Nevertheless, to rule out transfer pricing as the underlying reason for our findings, we limit our sample to acquired plants which do not report any transactions that could be used as a vehicle for transfer pricing (i.e., imports, exports or royalty payments). As reflected in Table 10 below, our earlier conclusions are confirmed even with the restricted sample size. The results suggests that even plants that do not engage in any foreign transactions experience a large and statistically significant productivity improvement (relative to the control group) following a foreign acquisition.

Table 10. Matching Results for Subsample of Plants with no Foreign Transactions

Effect of Foreign Acquisition	Log TFP (No foreign trade in t=0 and t=1)	Log TFP (No foreign trade in t=0 to t=2)	Log TFP (No foreign trade and no royalties in t=0 to t=2)
Acquisition year	0.339*	0.355*	0.257
	(0.17)	(0.21)	(0.19)
One year later	0.352**	0.323*	0.216
	(0.15)	(0.18)	(0.21)
Two years later	0.532**	0.602**	0.553**
	(0.21)	(0.24)	(0.26)
n	25	21	16

Average Treatment Effect on the Treated. Bootstrapped std errors in parentheses.
*, **, *** indicate statistical significance at the 10, 5 and 1% level, respectively.

[34] This conclusion is based on the corporate tax rates reported in the *Global Competitiveness Report* (1996). The comparison takes into account statutory tax rates as we have no information about tax incentives that may have been granted on a case-by-case basis.

(b) Could the observed changes be due to foreign acquisitions lessening credit constraints? While the transfer of know-how and technology accompanied by improvements in management is a plausible explanation for the results presented so far, benefits from foreign ownership could also work through easier access to financing. It is possible that foreign investors pick plants that would have done well in the absence of foreign ownership, had they had sufficient access to credit. For instance, foreigners may choose to invest in local plants that have recently developed a potentially successful new product or identified a promising investment opportunity but are unable to take advantage of it due to lack of financing. If this were the case, the sole impact of foreign investment would be provision of financing rather than transfer of knowledge. To address this possibility we accounted in the construction of the propensity score for having a bank loan as well for investment undertaken by the plant during the year preceding a foreign acquisition (see Table 2). Our matching analysis is thus conditional on these two variables. Neither of the two factors, however, appears to be a statistically significant predictor of a foreign acquisition.

To take this issue even further, we employ an alternative matching technique where we match plants on a Mahalanobis distance measure of the propensity score and the value of investment in the year of ownership change. This allows us to construct a new control group with the following characteristics: (i) similarity to the treament group in terms of observable characteristics (considered earlier) prior to the acquisition, and (ii) similarity in terms of investment undertaken *in the year when foreign investment is received.* The logic behind this exercise is that if plants from the same industry with similar observable characteristics exhibit a similar investment pattern in the same year, something other than credit constraints should be responsible for a divergence in performance. The results from the difference-in-differences approach applied to this new control group are presented in Table 11. They are very similar to those obtained earlier which suggests that credit constraints are unlikely to be driving our results.

Table 11. Matching on Mahalanobis Distance including Investment at t=0

Effect of Foreign Acquisition	Log Relative TFP	Log TFP
Acquisition year	0.158***	0.168***
	(0.06)	(0.05)
One year later	0.258***	0.277***
	(0.06)	(0.07)
Two years later	0.267***	0.294***
	(0.08)	(0.07)
n	119	119

Average Treatment Effect on the Treated. Bootstrapped std errors in parentheses.
*, **, *** indicate statistical significance at the 10, 5 and 1% level, respectively.

Finally, we check whether the acquired plants experienced a larger increase in the amount of outstanding loans than the control group. This does not appear to be the case. When we consider the value of outstanding loans (both domestic and foreign) normalized by the plant output, and we do not find a statistically significant difference between the two groups (see Table 12).[35]

Table 12. Matching Results for Loans/Sales

Effect of Foreign Acquisition	Loans/Sales
Acquisition year	-0.055
	(0.07)
One year later	-0.042
	(0.08)
Two years later	-0.038
	(0.08)
n	179

Average Treatment Effect on the Treated. Bootstrapped std errors in parentheses. *, **, *** indicate statistical significance at the 10, 5 and 1% level, respectively.

(c) Can capacity utilization explain the observed productivity improvements?

In order to ascertain whether the changes taking place in the acquired plants are part of a long-term restructuring process, or whether they are short-term expansions of the production scale resulting from the provision of new markets, we also apply the matching analysis to the self-reported information on capacity utilization. As evident from Table 13 below, changes in capacity utilization alone cannot explain the improvements in performance experienced by plants receiving FDI. In the year of acquisition, there is no statistically significant divergence in capacity utilization between the two groups. In the subsequent year, FDI recipients increase their capacity utilization relative to the control group, but two years after the acquisition the difference disappears. Even in the period where the effect is significant at the 10 percent level, however, the average increase in capacity utilization amounts to only 8 percentage points, from 65 to 73 percent.

Table 13. Matching Results for Capacity Utilization

Effect of Foreign Acquisition	Capacity Utilization (%)
Acquisition year	4.32
	(4.62)
One year later	9.89*
	(5.35)
Two years later	8.12
	(5.50)
N	133

Average Treatment Effect on the Treated. Bootstrapped std errors in parentheses. *, **, *** indicate statistical significance at the 10, 5 and 1% level, respectively.

[35] To remove outliers, we drop plants with the loan to output ratio above 10.

Neither are our findings due solely to scale economies. The production functions estimated at the sectoral level indicate that in 77 percent of cases (or 48 out of 62 sectors) constant returns to scale cannot be rejected. Thus, we conclude that the results are consistent with foreign investors inducing deep structural changes in the way the acquired plants are run and cannot be explained by economies of scale.[36]

(d) Are we picking up the exporter effect?

Our results could potentially reflect the improvements stemming from a plant's effort to prepare for entering export markets, rather than the effect of FDI. To eliminate this possibility, we restrict our attention to the acquired plants that do not export in the acquisition year or the following years. Then we compare the performance of this subsample to the corresponding control plants in the same manner as we did before. This modification results in a very small change to the magnitude of the effect. As before, in all periods considered FDI recipients outperform plants remaining under domestic ownership (see Table 14).

Table 14. Matching Results for the Subsample of Plants with no Exports

Effect of Foreign Acquisition	Log TFP
Acquisition year	0.164**
	(0.08)
One year later	0.239***
	(0.08)
Two years later	0.295***
	(0.10)
n	102

Average Treatment Effect on the Treated. Bootstrapped std errors in parentheses. *, **, *** indicate statistical significance at the 10, 5 and 1% level, respectively.

(e) Is it foreign ownership per se or acquisitions in general?

While our data set does not allow us to test directly whether the observed productivity improvements stem from foreign ownership *per se* or would result from any (domestic or foreign) acquisition, we believe that the former explanation is much more plausible for several reasons. First, as explained earlier in the literature review, multinational corporations are characterized by large endowments of intangible assets relative to other firms in developed and, even more so, developing countries. Thus foreign acquisitions present a greater potential for technology and know-how transfer to the acquired plants than domestic takeovers.

Second, domestic M&A activities in Indonesia were quite limited during the time period considered in our study. According to the Securities Data Corporation Mergers and

[36] Little is known about the relationship between plant-level scale economies and multinationality. The available evidence suggests, however, a negative association (see references in Markusen 1995).

Acquisitions Database, there were only 47 domestic acquisitions between 1988 (the first year of data availability) and 1994, of which only 19 took place in manufacturing sectors.

Third, as illustrated in the Appendix, the few cases of cases of domestic M&As in manufacturing, for which data are available, suggest that foreign acquisitions may be associated with greater performance improvements than domestic takeovers. This view is also supported by the evidence from Malaysia presented by Fauzias and Shamsubaridah (1995) who find a statistically significant decline in the performance (measured in terms of earnings per share and return to capital) of establishments acquired by domestic companies.

Further evidence on the differential effect of domestic and foreign acquisitions comes from information on privatization episodes. Our data set does not allow us to identify changes in ownership if both the new and old owners are private Indonesian entities. However, we can observe previously state-owned plants being sold to domestic or foreign owners. We use this fact to compare the performance of formerly state-owned plants that were sold to foreign owners (treatment group) with that of plants sold to domestic interests (control group). Again the difference-in-differences approach is used. To create the control group we model the probability of a state-owned plant being privatized into foreign rather than domestic plants. Privatization is defined as a change leading to the public (central and/or local government) ownership share dropping to less than 20 percent. The explanatory variables in the probit model are the same as those listed in Table 2 with the exception of the public ownership dummy. As illustrated in Table 15 below, we find that previously state-owned plants acquired by foreign investors outperform those sold to domestic interests. The divergence in performance is statistically significant in the first and second year following the privatization. In the second year, the estimated advantage is equal to 35 percentage points which is only one percentage point higher than the effect estimated in our basic specification in Table 3.

Table 15. Matching Results for Privatization Cases (not restricted within sector/year)

From Public to Foreign Private vs. Domestic Private

Effect of Foreign Acquisition	Log Relative TFP
Acquisition year	0.241
	(0.16)
One year later	0.392**
	(0.17)
Two years later	0.303**
	(0.146)
n	39

Average Treatment Effect on the Treated. Bootstrapped std errors in parentheses. *, **, *** indicate statistical significance at the 10, 5 and 1% level, respectively.

(f) Are our results driven by the methodology chosen?
To eliminate the possibility that our results are driven by the methodology chosen, we use an approach employed by several existing studies (Griffith 1999; Harris 2002; Benfratello and Sembenelli 2002). We apply a GMM system estimator, proposed by Blundell and Bond (1999), to estimate a production function including a binary variable for foreign ownership. The production function is estimated separately for 62 industries of the Indonesian manufacturing sector. If foreign ownership has a positive impact on plant productivity, we expect to find a positive coefficient on the FDI variable.

The definitions of variables used in the estimation are the same as those employed earlier, except for the additional FDI dummy. Real output is the dependent variable and the explanatory variables include production labor, non-production labor, materials and capital as well as the FDI dummy. All variables on the right hand side (including FDI) are considered potentially endogenous and are instrumented by levels lagged 3 to 6 periods in the differenced equation and by differences lagged 2 to 6 periods in the levels equation.

A summary of the GMM results is presented in Table 16 below. The coefficient on the FDI variable shows a positive sign in 55 of the 62 industries. 73 percent of the acquired plants analyzed in Section 7 belong to industries where this effect is positive and significant at the 10 percent level. The estimated magnitude of the effect on the plant productivity averages at around 26 percentage points with the median effect of 23 percentage points. These estimates are broadly in line with the results presented in Section 7. The GMM results hence confirm our previous results that foreign ownership *per se* has a significant impact on plant productivity.

Table 16. GMM System Results (Blundell/Bond 1999):
FDI Indicator in Production Function

Number of industries with FDI	62
Industries with positive sign for FDI	55
Industries with positive sign for FDI, significant at 10% level	39
Industries with Sargan-Test not rejected at 5% level	44
Industries with Second-Order Autocorrelation rejected at 5% level	55
Number of FDI Recipients	185
Number of FDI Recipients in Industries with positive and significant sign for FDI	149
Average magnitude of the estimated effect of FDI on plant productivity	26 % pts
Overall Number of Observations in Estimation	99,964

8 Conclusions

A large empirical literature searches for the evidence of knowledge spillovers from foreign direct investment. Implicit to this analysis lies the assumption that foreign ownership *per se* conveys some intangible advantages whose proximity can be beneficial to domestic firms. Yet there is no robust empirical confirmation that this assumption holds.

This study fills this gap in the literature by examining the causal relationship between foreign ownership and plant productivity using a Census of Indonesian Manufacturing Plants. Our aim is to distinguish between the possibility of foreign investors acquiring above-average performers (the gifted kids explanations) and genuine performance improvements resulting from foreign ownership (the pushy parent hypothesis). To make a clear distinction between correlation and causality, our analysis focuses on plants that change from domestic to foreign ownership and combines the difference-in-differences approach with a propensity score matching.

The results suggest that foreign ownership brings significant benefits to Indonesian plants. The acquired plants experience a faster growth in total factor productivity than their counterparts remaining in domestic hands. They also grow faster in terms of output and employment, invest more and increase employee wages faster. Finally, they become more integrated into the international economy, both in terms of exports and in terms of sourcing inputs from abroad.

Many developing countries strive to attract FDI inflows in the hope of stimulating economic growth through knowledge transfer associated with foreign investment. Recently, the *Economist* magazine pushed this view even further by stating that "the fate of the [Indonesian] economy rests on attracting foreign investment."[37] The positive view of FDI and benefits it may bring to Indonesia and other developing countries are reinforced by the results of this study which indicate that foreign investors outperform indigenous plants and that foreign ownership *per se* lies at the root of this advantage. This finding is important as the existence of a positive direct effect is a precondition for knowledge spillovers from FDI.

[37] "Time to deliver: A survey of Indonesia." December 11, 2004, p. 4.

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Appendix

Additional Evidence on Domestic vs. Foreign Acquisitions in Indonesia

The Securities Data Corporation Mergers and Acquisitions Database lists 47 domestic acquisitions in Indonesia between 1988 (the first year of data availability) and 1994 (the last year in which acquisitions are considered in our sample), of which 19 took place in manufacturing sectors. For 6 of the 19 cases we managed to obtain additional data from the *Worldscope* database (1995 release). As *Worldscope* does not contain sufficient information to calculate TFP figures, in the table below we consider the evolution of the ratio of cost of goods sold (COGS) to sales, which gives some indication of the efficiency with which inputs are being utilized. The COGS is defined as the wage and material costs. The ratio of COGS to sales is normalized by the average value observed in a given industry and year. The industry averages are calculated based on the data from the Indonesian Census of Manufacturing. For comparison purposes, we calculate the analogous figures for the plants acquired by foreign investors, considered in Section 7.

The available information, albeit limited, suggests that foreign acquisitions may be associated with greater performance improvements than domestic takeovers. A performance improvement is defined as a decrease in the ratio of COGS to sales (relative to the industry average). Out of six firms considered, only two experience a decline in the ratio and the decline does not take place until two year after the acquisition. Thus on average a domestic acquisition is associated with a deterioration in firm performance. In contrast, plants which undergo foreign acquisitions (considered in Section 7) experience on average a decline in the ratio in the year of the acquisition as well as in the following period. Two years after the takeover the ratio increases slightly but remains well below the pre-acquisition period.

Table 1A. Cost of Goods Sold over Sales, normalized by the industry average

	t-1	t=0	t+1	t+2
Domestic Acquisition 1	0.593	0.912	1.214	1.269
Domestic Acquisition 2	1.153	1.149	1.176	1.116
Domestic Acquisition 3	1.062	1.026	1.087	1.102
Average of 1- 3	0.936	1.029	1,159	1.162
Domestic Acquisition 4		0.561	0.726	0.833
Domestic Acquisition 5		0.811	0.961	0.924
Domestic Acquisition 6		0.736	0.974	1.068
Average of 4 - 6		0.703	0.887	0.942
Overall average (1 – 6)		0.866	1.023	1.052
Foreign Acquisitions	0.939	0.925	0.885	0.901

The figures on domestic acquisition come from the Worldscope database, while the figures for foreign acquisitions are from the Indonesian Census of Manufacturing.

CHAPTER 2.

Export Behavior and Firm Productivity in German Manufacturing: A firm-level analysis[38]

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 export 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 a growing 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 (2003), 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 a full geographical coverage of Germany.[39] 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) that we use is estimated from firm input and output data, correcting for some potential sources of bias in TFP estimation. Since firms observe their respective productivities that are unobserved by the researcher, they may take this knowledge into account when making their input choices – which in turn are observed and used for the productivity estimation. As a result, there is likely to be a

[38] This Chapter is joint work with Katrin Hussinger. I am indebted to Giorgio Barba Navaretti, Laura Bottazzi, Dirk Czarnitzki, Christopher Flinn, Georg Licht, Gianmarco Ottaviano, Cyrille Schwellnus and an anonymous referee for helpful comments. I also thank the team of the Mannheim Innovation Panel (Sandra Gottschalk, Bettina Peters, Christian Rammer and Tobias Schmitt) for providing data. All remaining errors are mine.

[39] 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.

correlation between the error terms and the explanatory variables in the estimation equation, which implies that least-squares estimation procedures would produce biased coefficient estimates. Therefore, we estimate total factor productivity at the firm level in a way, that is robust to this simultaneity bias from endogenous 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. However, the positive correlation between firm productivity and exporting that we find does not answer the question of 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 two empirical methods: First, we use the concept of Granger causality to test for causal relationships in both directions. We find that TFP granger causes a firm's export status, and not vice-versa. We also document some descriptive evidence about the productivity trajectory of newly exporting firms with respect to their entry date into foreign markets. This descriptive evidence shows that firms have a productivity advantage before they become exporters, and productivity does not improve after export market entry. Second, we employ a non-parametric matching technique to explicitly test for the direction of causality opposite from the one we found in the Granger test. The matching analysis examines whether exporting is at all effective for improving firm performance, taking into account that the subgroup of exporting firms is not a randomly selected sample.[40] This is necessary because our previous results suggested that exporters self-select themselves into selling abroad because they were high performers in the first place. The 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 productivity gains from exporting, points at re-allocation as the primary source behind aggregate productivity gains caused by exports.

[40] Using matching techniques in the context of firm exports is relatively novel. Only Wagner (2002) and Girma et al. (2004) have used similar methods so far.

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, 2004), 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 2002), 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).[41] The empirical literature finds a robust positive correlation between productivity at the firm level and exporting. Only part of this literature, however, looks at the direction of causality between firm productivity and export status, and thus goes beyond an 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 stresses 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) find 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 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 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 far as the technological argument is concerned, one might expect the learning hypothesis to have more explanatory

[41] This list makes no claim for completeness.

power for countries facing significant technological gaps vis-à-vis the foreign markets, which may be less relevant for firms from Germany, a technologically advanced economy. 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 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 (2002) 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. Girma et al. (2004) also find learning effects for export market entrants in Great Britain. 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 firm 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.[42] The

[42] A detailed description of the Mannheim Innovation Panel for the German Manufacturing sector can be found in Janz et al. (2001). German privacy legislation prohibits the disclosure of micro data, even for purposes of academic research. To guarantee privacy to the firms participating in the survey, only an anonymized version of the MIP available to external researchers. See Gottschalk (2002) for more details. This study uses the original data.

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.[43] This study uses an unbalanced panel of 2,149 observations at the firm level, which corresponds to 389 firms, 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.

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 the middle of 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 sample shipments or border proximity and focus instead on systematic and significant foreign sales activities.[44] 1,260 observations belong to exporting firms. 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 estimate a two-factor logarithmic Cobb-Douglas production function containing labor and capital as production factors, and construct our TFP measure from the residual of each observation.[45] Using ordinary least squares methods is likely to produce biased coefficient 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, and hence 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 (1999a) and Pavcnik (2002), we employ a semi-parametric estimation technique following Olley and Pakes (1996) to get consistent estimates of TFP. This estimation method uses investment outlays

[43] Firm-level data sets typically have the problem that only firms above a certain size are included in the sample. This is not the case for our data: in fact our smallest firm has two employees. However, large firms are overrepresented in the sample. Since large firms are a heterogeneous group but have a strong influence on the sample means, their sample probability in the MIP was deliberately set higher than that of small firms. Our sample means lie about 34% above average published in the official statistics in terms of employment, and 20% above in terms of firm sales. This also implies a proportion of exporting firms that is higher than in the entire population of firms.

[44] Our qualitative findings are robust to lowering this threshold level. In particular, we tried specifications with a 2.5%, 1% and 0% threshold definition of exporters. The only change when doing so was a reduction in the level of significance for the influence of TFP on exporting in the Granger tests reported in Table 3.

[45] We have repeated this procedure for a more flexible translog production function, and the results were very similar.

of the firm as a proxy for unobserved productivity shocks, and thus produces coefficient estimates that are robust to the presence of simultaneity and unobserved heterogeneity in production, without significantly increasing the computational burden.[46] The Appendix 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.[47] 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. This specification allows us to focus on firm heterogeneity within industries.

A comparison of our TFP estimates between exporters and non-exporters in Table 1 reveals important exporter premiums 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 on 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.

Table 1: Descriptive Statistics of Exporters and Non-Exporters

Variable	Exporters	Non-Exporters
TFP	1.51	1.10
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
Number of Observations	1260	889

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

[46] 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 method used would in principle allow for this.
[47] These groups are formed y NACE2-Codes 15, 16-22, 23-28 and 29-37.

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 Jensen (2004) 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.[48] 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, and draws on Bernard and Jensen (1999). In the absence of sunk costs, a rational profit-maximizing firm exports if the

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

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:

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

where p is the export price, q the exported quantity, c are additional production costs of producing the exported quantity q.

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:

$$V_{it} = \max_{EXP_{it}\in\{0,1\}}\left(p_{it}\cdot q_{it} - c_{it}\left(X_{it}, q_{it}\right) - S\cdot\left(1 - EXP_{it-1}\right) + \delta\cdot E\left(V_{it+1}\right)\right) \tag{2}$$

where delta is a discount factor, S are sunk costs of exporting and EXP_t is a binary variable indicating whether a firm exports or not in period t. The solution to this problem is the decision rule

$$EXP_{it} = \begin{cases} 1: & p_{it}\ q_{it}\ - c_{it}\ (X_{it}, q_{it}\ ) + \delta\cdot\left[E(V_{it+1}\mid EXP_{it}=1) - E(V_{it+1}\mid EXP_{it}=0)\right] > 0 \\ 0: & \textit{otherwise} \end{cases} \tag{3}$$

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:

$$P(EXP_{it}=1)=\Phi(TFP_{t-1},\ size_{t-1},\ RD_{t-1},\ NP_{t-1},\ skills_{t-1},\ east,\ young,\ D_{it}) \tag{4}$$

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. 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.

Table 2: Probability of Exporting

Probit Estimates	Complete Sample	Only non-switchers
Dependent Variable: Exporter 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 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 and 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.

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

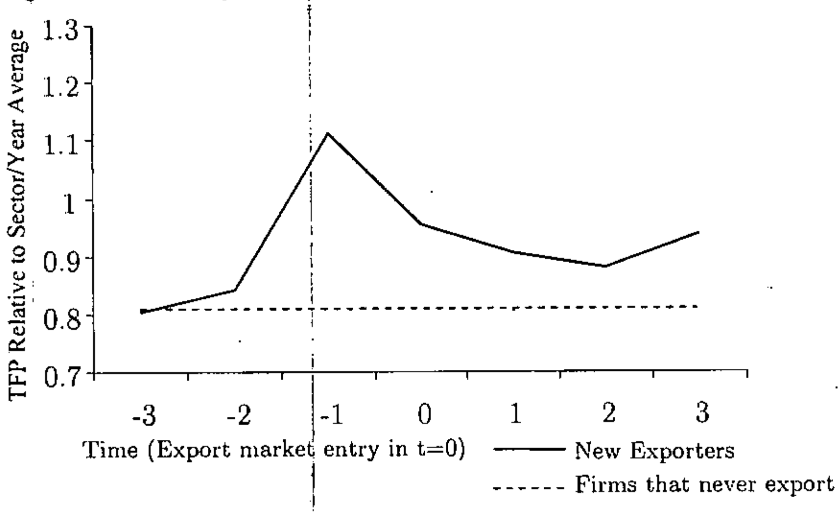
The results from this specification are qualitatively very similar to the previous ones, with generally higher levels of statistical significance of the coefficient estimates. Again, productivity significantly increases the odds of exporting, as do firm size and R&D intensity. The share of new products 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 odds 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.

Figure 1: TFP Trajectory of New Exporters



At time t-3, the future export starters are part of the group of non-exporters Their average productivity at t-3 is almost equal to the one of those firms that will not take up exporting later on. In the two periods preceding the export market entry, future exporters experience a significant rise 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.[49] Still, we interpret these patterns as descriptive evidence that our new exporters may well have taken their initial export

[49] Such a comparison is the basic approach for causal inference in Bernard and Jensen (1999).

decision in reaction to their performance trajectory, while it is unlikely that their TFP benefited largely from the export decision itself.[50]

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 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:

$$TFP_{it} = \sum_{j=1}^{2} \beta_j^1 \cdot TFP_{it-j} + \sum_{j=1}^{2} \gamma_j^1 \cdot EXP_{it-j} + \kappa_i^1 + \varepsilon_{it}^1 \qquad (5)$$

$$EXP_{it} = \sum_{j=1}^{2} \beta_j^2 \cdot TFP_{it-j} + \sum_{j=1}^{2} \gamma_j^2 \cdot EXP_{it-j} + \kappa_i^2 + \varepsilon_{it}^2 \qquad (6)$$

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 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.[51]

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[50] 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.

[51] 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 percent. Performance history, however, is not a significant predictor for marginal exporters. When cutting the threshold definition of exporters to 2.5 percent of output exported, the performance history was significant only at a confidence level of 90 percent. For 1 percent, this confidence levels was reduced to 89 percent. Hence, firms that only send minimal shipments abroad are not characterized by an exceptional performance history.

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

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 correct, 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.

This setup bears close resemblance to situations encountered in the microeconometric evaluation of active labor market policies, as surveyed in Heckman et al. (1999) and Blundell and Costa Dias (2000).[52] 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.

[52] 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" 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 often called the Average Treatment effect on the Treated (ATT), and can be given a causal interpretation.

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.[53] 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.

Our matching technique is one-to-one nearest neighbor matching, i.e. it undertakes comparisons within pairs of observations, conditional on a vector X.[54] 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).[55] 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.[56] The matching is implemented in Stata 8 using the psmatch2 procedure suggested 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, a

[53] Out of 2,037 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.

[54] 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% of the treatment observations, symmetry could not be rejected at the 1% significance level.

[55] See Rosenbaum and Rubin (1983) for a proof that matching on the propensity score is an appropriate means of overcoming the difficulty of determining similarity of observations in a multidimensional space.

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

condition often referred to as 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.

Table 4 : Matching Results

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

Standard errors are bootstrapped.

In other words, as we take into account the non-random selection 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.

As a robustness check, we also consider productivity growth from the period prior to the export market entry one and two years ahead. This amounts to a combination of matching with a difference-in-differences analysis. Looking at productivity growth instead of levels, we find that the average TFP growth of exporters is slightly slower than for non-exporting firms, both in the matched and the random sample.[57] This holds both for the one-year growth rate and the cumulative two-year growth rate. 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. 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 of our matching analysis, we conclude that once we control appropriately for selection into the treatment group, there are no significant TFP differences between exporters and non-exporting firms. In other words, there is no causal effect from exporting towards TFP, neither in levels nor in growth rates over one or two years following the start of export activities. 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 examine the causal 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 there is 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.

[57] 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.

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. The matching method controls for the non-random selection of exporting firms in our sample, and allows us to 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 2003, 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 productivity-related reason why German policy makers should prefer foreign sales over domestic sales. Wherever policy aims at creating new exporters that have not to date been exceptional performers, there is 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 become better performers once they are active in foreign markets.

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Appendix. 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:

$$y_{it} = \beta \cdot l_{it} + \gamma \cdot k_{it} + u_{it} \qquad (7)$$

In this equation, the estimated error term u_{it} represents 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.

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

$$K_{it+1} = (1-\delta)K_{it} + I_{it} \qquad (8)$$

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 the error term u_{it} in (7) that is observed by the firm early enough to influence the investment decision:

$$i_{it} = i_t(\varpi_{it}, k_{it}) \qquad (9)$$

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

$$y_{it} = \beta \cdot l_{it} + \phi(i_{it}, k_{it}) + e_{it} \qquad (10)$$

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

$$y_{it} - \beta \cdot l_{it} = \gamma \cdot k_{it} + g(\phi_{t-1} - \gamma \cdot k^{*}_{t-1}) + e_{it} \qquad (11)$$

where g is an unknown function that is again approximated by a third order polynomial expression in ϕ_{t-1} and k_{t-1}. The consistent factor coefficient estimates allow us to construct the residuals of (7).

CHAPTER 3

Exports versus FDI in German Manufacturing: Firm Performance and Participation in International Markets [58]

1 Introduction

It is a well-established empirical fact that even within narrowly defined manufacturing industries, firms display considerable heterogeneity with regard to the extent to which they serve foreign markets. While some firms do well serving only their home market, others are able to generate additional gains in export markets, or find it profitable to set up a foreign subsidiary in order to produce for demand in foreign countries. Both the 'traditional' and 'new' trade theories rely on representative firms and are thus unable to explain how firms belonging to the same sector can display heterogeneous behavior. However, a recent strand of theory initiated by Melitz (2004) and Bernard et al. (2003) has been able to explain heterogeneity with respect to foreign trade in a formal framework. Firm heterogeneity is traced back to innate differences in productivity levels, which are modeled as draws from a common distribution function. Helpman, Melitz and Yeaple (2004) (henceforth HMY) extend the framework of Melitz (2004) to incorporate the possibility that firms engage in foreign direct investment (FDI). One of the key predictions of their model is a productivity ordering of firms according to their patterns of participation in international commerce.

In the theoretical model, firms receive a random productivity draw from a given distribution. Subsequently, entrants self-select themselves into one of 34 categories depending on the outcome of their draw. Entrants may produce for the domestic market only, export or establish a foreign subsidiary. Increasing participation in international markets is a strictly monotonous function of a firm's productivity: Low productivity firms serve only the home market, while better performers can afford to pay the additional fixed cost of expanding their market towards foreign buyers through exporting. Finally, the highest productivity draws will establish production plants in foreign markets, and thus engage in horizontal foreign direct investment (FDI).[59] It is this productivity ordering that we test in this paper, using firm-level data from the German manufacturing sector.

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[58] This chapter is joint work with Katrin Hussinger. I am indebted to Beata Javorcik, Gianmarco Ottaviano and Lucy Payton for useful comments, as well as to seminar participants at the Deutsche Bundesbank and the European Trade Study Group Conference. I would like to express my gratitude to the Deutsche Bundesbank and the team of the Mannheim Innovation Panel for providing data. Moreover, I thank Thorsten Doherr for employing his search engine for the data merge, and Fred Ramb for assistance with the data.

[59] Licensing arrangements are not a predicted pattern of this model, and are not dealt with in this paper. An additional prediction of their model, which is not examined here either, is that FDI will be relatively more prominent in sectors with higher dispersion of firm productivities.

While theoretically attractive, and thus far the only theoretical explanation of firm heterogeneity with respect to both trade and investment, the HMY model still lacks a solid empirical foundation. Most of the existing empirical evidence covers only parts of the heterogeneity explanations offered by HMY. For instance, it has been documented that exporting firms tend to outperform non-exporters, and that subsidiaries of multinationals are more productive than domestic firms in the host country.

The scarcity of comprehensive empirical evidence so far may be due to the fact that micro-data with records on export behavior and outward foreign investment on the same firms are not readily available for many countries. This paper makes use of a newly merged dataset on German manufacturing firms to test the model predictions using the concept of stochastic dominance. Rather than comparing first moments alone, this concept tests for differences over the entire distribution of firm productivities. Intuitively, a distribution dominates another one if its cumulative distribution function lies entirely to the right of the other one. Stochastic dominance can be tested non-parametrically using one- and two-sided Kolmogorov-Smirnov tests (KS-tests). In our eyes, this empirical concept is close in spirit to the self-selection mechanism in the HMY model. We apply these tests to the distribution of total factor productivity (TFP) of German firms. Our TFP estimates are obtained using a semi-parametric estimation technique following Levinsohn and Petrin (2003). This estimator delivers consistent estimates even in the presence of a possible correlation of factor input choice and unobserved shocks to productivity.

Our results display a remarkable fit of the productivity distributions of German firms with the pattern predicted by the HMY model. Exporting firms clearly outperform non-exporting firms over the entire productivity distribution, and the same holds for German multinational firms vis-à-vis the former group. The empirical confirmation of the rank ordering of firms with different patterns of international commerce in terms of productivity is a novel empirical result, and is consistent with the mechanisms at work in the HMY model.

2 Theory

The firm choice between exporting at arms' length and foreign direct investment has traditionally been modeled as a proximity-concentration trade-off (Brainard 1993, 1997). Increasing returns to scale at the plant level create incentives to concentrate production in one place, while transaction costs associated with distance between the locations of production and sale provide a countervailing force towards establishing a production plant closer to the foreign market. This trade-off has found support in data at the industry level, but it cannot explain heterogeneous choices of firms within sectors.

In the heterogeneous firms model by Helpman, Melitz and Yeaple (2004), firms within each sector display heterogeneous levels of productivity. Decisions are made according to the following sequence: Potential entrants pay a sunk cost f_E in order to enter an industry. Upon paying this sunk cost, which has almost the interpretation of a lottery ticket, an entrant receives a random productivity draw in the form of a labor input coefficient a per unit of output from a known distribution $G(a)$.[60] Having learned about its draw, a firm may decide to leave the market altogether (in which case it has profits $\pi = -f_E < 0$ and will ex post regret having participated) or to pay an additional fixed cost f_D of setting up production at home. After paying the fixed cost f_D the firm produces a unique variety of a differentiated good for the home market at a marginal labor cost equal to its productivity draw a.

The degree of participation in international markets that a firm chooses is governed by the following parameters: An additional fixed cost f_X has to be incurred in order to export, while setting up a foreign production plant has a (higher) fixed cost of f_I. The concentration force is embodied in the difference between these two parameters, whereas the proximity force stems from the fact that exporting adds to marginal cost by commanding iceberg-type transport costs of $\tau>1$ per unit of output sold in the export market. That is to say, it is assumed that τ units of output have to be shipped in order for one unit to arrive at the foreign destination. Production by a foreign affiliate, on the other hand, does not incur per-unit transport costs and is produced using the same firm-specific level of efficiency a as in the home country.[61]

From this distinction between fixed and marginal costs assumed in the model, it becomes clear that the sales volume in the foreign country will play a crucial role in determining the optimal degree of internationalization of a firm. Suppose for simplicity that wages are equal between the two countries. Consumers are assumed to have CES preferences over differentiated products with an elasticity of substitution $1/(1-\alpha)$, and market structure is assumed to be monopolistic competition.[62] A firm's variety in a given market will then be priced at $p=a/\alpha$ if produced in the same country, or at $p = \tau\, a/\alpha$ if it incurs transport costs. It will face a demand $D^i = A^i\, p^{1/(\alpha-1)}$, where A^i is a measure of the market size of country i. Hence, regardless of how a firm decides to serve a market, its sales volume in that market will be a decreasing function of its marginal cost parameter a, or in other words a strictly increasing function of its productivity.

Since firms charge markups above unity and thus enjoy positive operating profits, the volume of sales determines a firm's ability to recoup the fixed costs associated with different choices. First, consider the decision to produce for the domestic market and incur fixed costs f_D. Only firms above a certain productivity threshold can expect a sales volume large enough to recoup f_D. Firms with a productivity below this threshold will hence decide not to enter the market. The marginal firm that decides to enter the domestic market,

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[60] It should be clear that the HMY model adds nothing to the understanding of which specific firm will have productivity advantages vis-à-vis its competitors because the draws are random. The contribution of the model lies in explaining how heterogeneous productivity levels and trade patterns can coexist in equilibrium rather than explaining the productivity and trade pattern of a specific firm.
[61] This holds true if there are no factor cost differences between the home and the host country. Head and Ries (2003) show that these can alter and in the extreme case invert the predictions of the model. In other words, the concept of FDI underlying the HMY model is a horizontal one, in which FDI is motivated by market access. Given that the overwhelming majority of the firms in our sample invest in other OECD countries (see section 4), it seems reasonable to test this model on our data.
[62] Head and Ries (2003) show that CES preferences and iceberg costs are not necessary to derive the results of the model. They use a quadratic utility function.

however, will find it unprofitable to serve a foreign market through exports: Since it faces higher marginal costs in that market due to transport costs, it will not be able to generate the sales volume necessary to recoup the additional fixed costs of exporting f_X in the foreign market. By the same token, it will not be able to pay $f_I > f_X$. Going up in the productivity ordering of firms, however, there will eventually be a firm whose expected sales volume meets the threshold necessary to expect positive profits in the foreign market from exporting, but not from FDI. Going further up in the productivity ranking, there will be a threshold firm whose expected sales volume in the foreign market is high enough so that it would rather pay the higher fixed cost f_I than the per-unit transport costs. This is the proximity-concentration tradeoff at the level of the firm, whose balance is determined by the sales volume of the firm in the foreign market, which in turn is a function of firm productivity.

Summing up, the model predicts three well-defined cut-off productivity levels: One at which firms decide to set up production in the home market, a second one at which they will export in addition to their domestic sales, and a third one at which FDI begins to dominate exporting. These cut-offs imply that firms with a productivity level above the highest threshold will engage in FDI, while a set of firms with productivity levels strictly below the FDI firms will export but not set up foreign affiliates. Finally, the productivity of purely domestic firms lies strictly below that of the exporting firms.

3 Related Empirical Literature

The present paper investigates the productivity patterns of firms that fall into three categories: Domestic non-exporters (D), domestic exporters (DX) and multinational firms with outward investment in a foreign country (DI). The argument entails two partial elements, which have been the subject of prior empirical research.

For one, an extensive empirical literature has investigated productivity patterns across exporting and non-exporting firms. Evidence is now available for a number of countries, including the United States (Bernard and Jensen 1999, 2004), the UK (Girma et al. 2004), Germany (Arnold and Hussinger 2005, also Fryges 2004 for a comparison of young high-tech firms in the UK and Germany), Taiwan and Korea (Aw et al. 2000) and for developing countries such as Chile (Pavcnik 2002), Colombia, Mexico and Morrocco (Clerides, Lach and Tybout 1998). The general message coming from this evidence is that exporters tend to outperform non-exporting firms, and that the causality mostly runs from productivity to export status.

Second, some studies investigate productivity differences between multinational companies and domestic companies both in the home and host countries. Doms and Jensen (1998) show that US multinationals have an above-average productivity with respect to all US companies. Yeaple (2005) shows that lagged productivity is a significant predictor of US firms establishing foreign subsidiaries, and Castellani and Barba Navaretti (2004) finds similar results for Italian companies. With respect to the host country, Arnold and Javorcik

(2005) show that foreign ownership has a significant positive effect on plant performance in Indonesia. Barba Navaretti and Venables (2004) provide a survey of the literature.

Apart from these studies lending partial support for the pattern suggested by theory, three studies undertake a more complete look at the issue. Head and Ries (2003) look at a sample of 1070 publicly listed Japanese firms for which they have information on exports and outward FDI. The study compares average TFP across firms with different degrees of internationalization, and finds some support for the predicted ordering, although the differences tend to be statistically insignificant. Head and Ries also estimate an ordered linear probability model, and again find mixed results. While the association between TFP and degree of internationalization is often positive, it is in many instances not statistically significant and on occasions even negative.

Girma, Görg and Strobl (2005) compare the productivity distributions of D, DX and DI firms in the Republic of Ireland, using data for the year 2000. Their study finds only partial support for the predictions from theory: They find no significant productivity differences between D and DX plants, while the productivity distribution function of DI firms statistically dominates the remaining two. However, their analysis is restricted to partial measures of firm productivity such as sales, value added and profit per employee. Lacking information on capital stocks of firms, they cannot control for possible underlying differences in capital intensity across the three groups of firms. Hence if firms with international engagement employ a more capital-intensive production technique, the findings run the risk of overestimating the performance of these firms.

Girma, Kneller and Pisu (2005) compare the productivity distributions of firms with different trade orientations using UK data. While this study examines total factor productivity (TFP) rather than labor productivity, the trade-related information in the principal data set used includes only information on the export status and on ownership. They make an effort to complement this with information on foreign investment activities from other sources, but are not able to achieve full systematic coverage of all firms in their sample with respect to FDI. Moreover, the information on foreign subsidiaries they gather is available only for one year, and is then backcast. They complement this analysis by examining foreign multinationals in the UK (on which they have full information for the latest year) rather than UK multinationals as the third category. While this is a clear departure from the theoretical model, it is expected to deliver similar results in the special case of symmetric countries. Their results are consistent with the HMY model for most but not all of the years in their observed time frame. Finally, Wagner (2005) analyzes information from personal interviews on a sample of firms from the German state of Lower Saxony for the year 1995 and finds supportive evidence for the HMY model using value added per worker.

Our paper represents an improvement on existing studies in several regards: For one, our data have a panel structure covering the years 1996 to 2002, and they are not restricted to publicly listed firms. We use a stratified sample including also small and medium enterprises, some of which tend to be heavily engaged in international activities in the German case. Second, our productivity measure is total factor productivity and not a partial productivity measure. Third, in contrast to other studies our productivity estimations control for a possible simultaneity bias in input choice by using a semi-parametric estimator suggested by Levinsohn and Petrin (2003). Fourth, we use reliable information on the foreign activities of German firms, which is collected by the German central bank on a mandatory basis. Using this information, we undertake comparisons of the entire TFP distributions of samples by testing for stochastic dominance, for each of the 7 years between 1996 and 2002.

4 Data and Descriptive Statistics

The data used in the present study come from two main sources, which have been merged for the first time. We use a rich array of firm-level information from a stratified, representative survey of the German manufacturing sector called the Mannheim Innovation Panel (MIP). The MIP is a yearly survey 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, which is conducted every fourth year. Started in 1992, the survey collects yearly information from manufacturing firms all over the country. The MIP contains information on firm-level output and export activities of each firm, in addition to several classes of production inputs.[63]

Our second data source complements this information with complete records on foreign subsidiaries of the firms in our sample. For this study, it was possible to merge firm records from the MIP with the micro-data base MiDi (Micro Database Direct Investment) provided by the German central bank (Bundesbank), which contains a complete listing of German direct investment stocks abroad.[64] Legal reporting requirements of the Foreign Trade and Payments Regulation ("Aussenwirtschaftsverordnung") guarantee the completeness of this information, for firms whose foreign assets exceed the effective exemption limits. In the case of minority participations these amount to € 5 million. For majority participations, branches and permanent establishments, any engagement exceeding a balance sheet total of € 500 thousand is subject to mandatory reporting to the Bundesbank. Indirect participating interests have to be reported if a primary direct investment branch has a holding of at least 10% in another firm or if the investing firm has participating interests larger than 50% of the capital shares or voting rights of the corresponding primary branch.[65] In our analysis, we consider any firm that reported either direct or indirectly held assets abroad as a multinational firm (DI type).

[63] A detailed description of the Mannheim Innovation Panel can be found in Janz et al. (2001). Note that this data set has been previously exploited in Arnold and Hussinger (2005) to test the causal relationship between firm productivity and export behavior. The findings of that study confirm the partial assessment that German exporters outperform non-exporting firms.

[64] See Lipponer (2003a) for a detailed description of this data base.

[65] Note that the reporting exemption limits changed in 1996 and in 2002, which influenced the number of records available (see Lipponer, 2003a, 2003b). Given that our analysis is done separately for each year, and covers the time period 1996-2002, our results are unlikely to be affected by this.

The merge process, for which sufficient identification information was available from 1996 on, was conducted using a computer-supported text field search algorithm, where matches are assigned according to firm names and addresses. Every potential match found by the search program was checked manually. The data set thus obtained is an unbalanced panel of 6,234 firm-level observations between 1996 and 2002, which corresponds to 2,148 firms. On average, there are 2.90 years of data per firm available. The data contain firms from all over Germany, including the former Eastern part of the country.

All three types of firms are present in each of the industries. With regard to international commercial relations, the largest subset of firms are exporting firms with no foreign investment (DX type). 4,092 observations belong to this group, among which are 1,499 firms with exports in each year. 660 observations belong to the DI type, which corresponds to 248 firms. 103 of those firms invest abroad in every sample year. We also observe the number of FDI projects a firm is engaged in for a given year. The mean of this number is approximately 6, while the median is only 2, implying a right-skewed distribution of the number of projects per firm. Most of the firms of type DI have at least one investment in the EU (72%) and in OECD countries (87%), which hints at a significant relevance of horizontal, market-seeking motivations for German outward FDI.

An interesting fact that emerged from the data was the absence of non-exporting firms with foreign assets in our sample, eliminating the need for a further distinction of firm types. All of the firms of the DI type had at least some exports, although we are not able to determine what proportion of these went to the foreign affiliate. The remainder of the sample consists of non-exporting firms with no foreign investment (D type), and comprises 1,482 observations.

Table 1: Descriptive Statistics by Type

Variable	Non-Exporters (D) N=1,482	Exporters (DX) N=4,092	FDI (DI) N=660
Number of employees	*74*	*440*	*3,223*
Sales	*9.67*	*76.63*	*688.10*
Value Added	*5.40*	*40.73*	*308.10*
Innovator (yes/no)	*16%*	*40%*	*55%*
R&D expenditure (if innovator)	*.23*	*2.37*	*38.03*
Share of sales from new products	*5%*	*7%*	*5%*
Total wage bill	*4.86*	*39.22*	*293.51*
Wage per employee	*.06*	*.07*	*.08*
Materials	*4.28*	*35.90*	*380.00*
East Germany	*48%*	*29%*	*7%*
Export turnover	-	*37.07*	*323.61*
Export intensity	-	*.28*	*.42*
FDI turnover	-	-	*420.31*
FDI intensity	-	-	*.86*
Number of FDI projects	-	-	*5.99*
At least 1 FDI project in EU	-	-	*72%*
At least 1 FDI project in OECD	-	-	*87%*

All monetary variables are measured in € millions.

Table 1 shows separate descriptive statistics for firms of the D, DX and DI type. On average, exporters are larger than non-exporters, both in terms of employment and sales or value added. Firms with foreign investment tend to be the largest of the three subsets. Interestingly, this ordering also carries over to the propensity to engage in R&D activities (the variable "Innovator"), and to the amount of investment into such activities. DX and DI firms also tend to pay higher wages to their employees, as measured by the total wage bill relative to the number of employees. Finally, table 1 also presents information on firm location, with the most interesting distinction for the case of Germany being the East-West divide. East Germany was a centrally planned economy up to 1989 and has been undergoing a transition process into a market economy since then. As several studies suggest, the process of catching-up of East German firms still is not yet completed (see Czarnitzki, 2005, as an example). In this light, it may seem of little surprise that in our (stratified) sample, the proportion of East German firms is highest in the subgroup of firms that serve only the domestic market, and decreases with increasing degree of internationalization.[66]

5 Empirical Strategy

The aim of this paper is to undertake performance comparisons across subsets of firms, defined by their degree of foreign engagement, with our measure of firm performance being total factor productivity (TFP). As a first step, we estimate TFP in the standard way, as the residual of a two-factor Cobb-Douglas production function. The value added of the firm is estimated as a function of labor and capital inputs. All nominal values are deflated using a set of sector-specific deflators from the German Federal Statistical Office. Our production function is estimated separately for each 3-digit sector of the Nace Rev. 1.1.[67]

A number of caveats apply when estimating firm-level productivity. First, partial productivity measures such as labor productivity are biased if there are systematic differences in capital intensity across the subsets of firms to be analyzed. This is a possibility that we cannot rule out in our specific case, which is why we abstain from using partial productivity measures. A second challenge arises due to the fact that firms can observe shocks to their own productivity about which the researcher does not know, and make their factor input choices contingent on these shocks. Such a behavioral pattern would cause the orthogonality of our explanatory variables and the error term (our TFP estimate) in our data to be violated, and thus render OLS estimation techniques invalid. This well-known problem is usually referred to as the simultaneity bias (Marschak and Andrews, 1944). We address this issue by using a semi-parametric estimator, in which a proxy variable is used to account for unobserved productivity shocks.

[66] In order to avoid the possibility of picking up East-West differences rather than differences in international commerce, we will repeat all the subsequent exercises excluding firms from East Germany. This never affected our results significantly.

[67] Some sectors had to be grouped together to achieve a sufficiently large number of observations for every estimation. Details on our industry aggregation can be found in the appendix.

The literature makes several suggestions for the choice of proxy: Olley and Pakes (1996) suggest the use of firm investment, while Levinsohn and Petrin (2003) propose material inputs of the firm instead. Our choice fell on the latter procedure, for several reasons. For one, not all firms have strictly positive investment in all periods, but only those observations may be retained in order for the procedure to be valid. In our case, this would imply a significant loss of observations. Material inputs, on the other hand, are strictly positive in all cases. Second, material inputs are less likely to be subject to indivisibilities and we would hence expect them to follow more closely any unobserved changes in firm productivity. We estimate production functions at the 3-digit level employing the Levinsohn and Petrin procedure, and use the residuals from these estimations as our estimates for firm-level TFP. In order to compare TFP estimates resulting from different sector-wise estimations, and to focus our attention on firm heterogeneity within sectors, we divide our TFP measure by the average TFP in the respective industry and year, and refer to the measure thus obtained as relative productivity.[68]

In order to undertake these kinds of comparisons, we invoke the concept of first order stochastic dominance.[69] Suppose we have two independent random samples of productivity realizations. One sample $\omega_1, \ldots, \omega_n$ is drawn from a distribution function Ω_1 and the other sample, $\omega_{n+1}, \ldots, \omega_N$ is drawn from another distribution function Ω_2. The hypothesis of interest is that $\Omega_1(\omega)-\Omega_2(\omega) \leq 0 \;\forall\; \omega \in \Re$. If this hypothesis holds, and the inequality is strict for at least some $\omega \in \Re$, we say that Ω_1 dominates Ω_2 stochastically. More intuitively, this is to say that the cumulative distribution function of a variable in the first random sample lies entirely to the right the corresponding cumulative distribution function in the other random sample.

Girma et al. (2005) consider an interesting extension of the HMY model. They note that if one relaxes the assumption of deterministic and fixed productivity levels and assumes each period's productivity realization to be subject to a random shock, regions of uncertainty may arise around the threshold productivity levels. In these regions, firms with similar productivity levels may make different choices, creating some overlap between the productivities of firms from different categories that is not present in the original model. As long as the self-selection mechanism remains an essential determinant of a firm's participation in international markets, stochastic dominance would continue to hold in such a setting. The concept thus remains a valid means of examining the rank ordering predicted by the model, even in the presence of some degree of uncertainty.

Stochastic dominance can be tested by evaluating two related null hypotheses. The first step is to reject the equality of distributions as in the null hypothesis

$$H_0: \; \Omega_1(\omega)-\Omega_2(\omega) = 0 \quad \forall\; \omega \in \Re.$$

[68] Hence an average-performing firm will have a relative TFP of exactly one.
[69] Although the concept of stochastic dominance dates from the 1930s, its first application in the context of international economics can be found in Delgado et al. (2002).

This is the two-sided Kolmogorov-Smirnov test, for which the asymptotic distribution of the test statistic has been derived by Kolmogorov (1933) and Smirnov (1939) under the assumption of independently drawn samples. If equality of the distributions over samples can be rejected, and at the same time one cannot reject the corresponding one-sided test that

$$H_0': \ \Omega_1(\omega)-\Omega_2(\omega) \leq 0 \quad \forall \ \omega \in \Re.$$

then one can conclude that $\Omega_1(\omega)$ stochastically dominates $\Omega_2(\omega)$. The asymptotic distribution of the corresponding test statistic is also known for the one-sided test under the condition that both samples are independent. Since we are using panel data which include repeated observations of the same firms, the independence assumption is likely to be violated if we pool observations from several years. For that reason, we run the KS-tests separately for each year from 1996 to 2002.

6 Results

The two- and one-sided KS-tests allow us to formalize two kinds of comparisons between subsets of firms. First, we compare the productivity outcomes between D and DX firms. As a second step, we compare DX and DI firms. If in both cases, the two-sided test is rejected while the one-sided test is not, then we can establish a clear ranking of the three samples by transitivity, and conclude that the productivity distribution of DX firms dominates D firms, while the distribution DI dominates both DX and D firms.

The results from the two- and one-sided KS-tests are displayed in table 3. Column 4 of table 3 presents the results of the two-sided tests for the equality of the distribution between D and DX firms. This null hypothesis can be easily rejected for all years. The one-sided test statistic in column 5, on the other hand, is not significant at conventional levels, meaning that we cannot reject H_0'. This is to say that we cannot reject the null that exporters are the higher productivity group. In other words, DX firms outperform D firms over the entire productivity distribution. The same kind of results for the comparison between DI and DX firms are displayed in the two rightmost columns of table 4. Again, we can conclude stochastic dominance of the group of firms with the stronger foreign engagement.

Table 2. Distributions of Productivity Levels.
Kolmogorov-Smirnov tests for Non-Exporters (D) vs Exporters (DX).

Year	No. of D firms	No. of DX firms	Two-sided KS test statistic (H_o) Equality of Distributions	One-sided KS test statistic (H_o') DX larger group
1996	215	830	0.1562 (0.00)	-0.0103 (0.96)
1997	345	747	0.2026 (0.00)	-0.0094 (0.96)
1998	345	749	0.2133 (0.00)	-0.0107 (0.95)
1999	145	434	0.2358 (0.00)	-0.0116 (0.97)
2000	142	418	0.2202 (0.00)	-0.0215 (0.91)
2001	145	453	0.1944 (0.00)	-0.0099 (0.98)
2002	145	461	0.1904 (0.00)	-0.0144 (0.96)

P-Values in parentheses.

Table 4. Distributions of Productivity Levels.
Kolmogorov-Smirnov tests for Exporters (DX) vs Multinationals (DI).

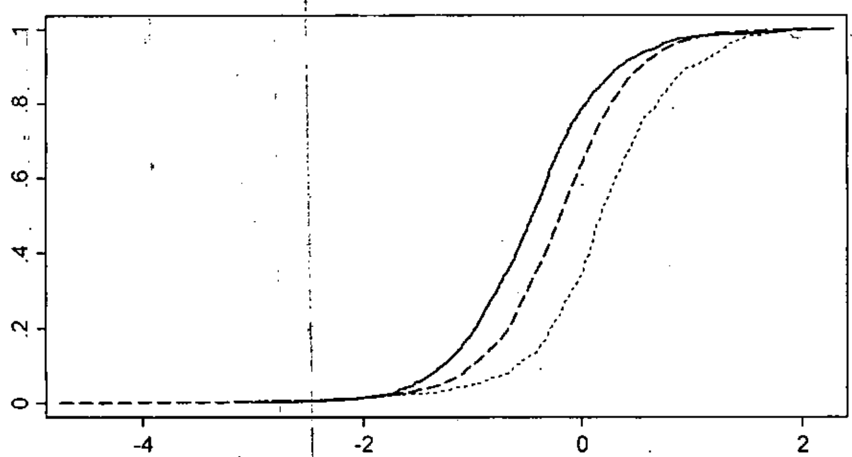
Year	No. of D firms	No. of DX firms	Two-sided KS test statistic (H_o) Equality of Distributions	One-sided KS test statistic (H_o') DI larger group
1996	830	115	0.3817 (0.00)	-0.0051 (0.99)
1997	747	142	0.3044 (0.00)	-0.0161 (0.94)
1998	749	144	0.2797 (0.00)	-0.0142 (0.95)
1999	434	61	0.2287 (0.01)	-0.0195 (0.96)
2000	418	66	0.2257 (0.01)	-0.0096 (0.99)
2001	453	72	0.3971 (0.00)	-0.0212 (0.95)
2002	461	60	0.4260 (0.00)	-0.0145 (0.98)

Asymptotic P-Values in parentheses.

These results confirm the productivity ranking of firms postulated by theory. As predicted by the HMY model, exporting firms are better performers than firms that produce for the domestic market only, while firms with foreign subsidiaries are the most productive of the three groups. The patterns present in our dataset of German manufacturing firms are thus consistent with the self-selection hypothesis underlying the HMY model.

Figure 1 gives an illustration of the intuitive meaning of these test. It depicts the cumulative distribution functions (CDF) of TFP for the three subsamples D firms (domestic sales only), DX firms (exporters) and DI firms (firms with investment abroad). The productivity ordering suggested by theory becomes apparent in this graph: The CDF of DI firms lies entirely to the right of that of DX firms, whose CDF in turn lies entirely to the right of the one corresponding to firms of the D type. The difference between DI firms and DX firms is slightly larger than the one between DX and D firms.

Figure 1. Cumulative Distribution Functions of TFP for the three firm types.



Given the particular case of Germany with its different recent economic history between the western and the eastern part of the country, we want to make sure that our analysis is not influenced by differences between East and West. In particular, one might conjecture that East German firms suffer from a productivity disadvantage vis-à-vis their western counterparts, while at the same time being less involved in international markets. For this reason, we repeated the analysis after dropping all East German firms from our sample. All our previous results are qualitatively the same when using a reduced sample of West German firms only.[70]

7 Conclusion

In this paper, we have used a representative sample of German manufacturing firms to test a prediction of a recent theoretical paper in the theory of international trade with heterogeneous firms. Helpman, Melitz and Yeaple (2004) predict that it is the more productive firms that can afford to pay the fixed costs of serving foreign customers via exports. Moreover, only the top performing firms find it profitable to pay a further fixed cost of setting up foreign establishments to be closer to their foreign customers.

[70] In fact, these results are so similar to the main results presented in tables 3 and 4 that we refrained from presenting them here. They are available from the authors upon request.

To analyze this proposed pattern empirically, we estimate firm total productivity for 43 German manufacturing sectors using a semi-parametric estimator following Levinsohn and Petrin (2003) to control for a possible simultaneity bias of input choice. We then use a non-parametric testing technique to rank the distribution of total factor productivity across the three subsets of firms, as defined by their engagement in international markets. Rather than just comparing first moments, these Kolmogorov-Smirnov tests allow us to make statements about the entire distribution of productivity across groups, using the concept of stochastic dominance.

Our data display a significant amount of within-sector firm heterogeneity with respect to productivity. The predicted threefold ordering of firm productivity according to the firms' trade orientation is compatible with our German data. We show that German exporters outperform firms that serve only the domestic market over the entire productivity distribution. In a similar manner, German multinational firms, defined as firms with subsidiaries abroad, are more productive than both domestically focused and exporting firms in Germany. These findings hold true for each year from 1996 to 2002. Our results thus lend strong empirical support for one of the key predictions of the theoretical approach of Helpman, Melitz and Yeaple (2004) for the case of German manufacturing.

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Appendix. The industry grouping used in our TFP estimations.

Industry	NACE 3
Food Products and Beverages	*151-159*
Other Food Products	*158*
Beverages, Tobacco Products	*159-160, 171, 175, 180, 200, 211, 212*
Preparation and Spinning of Textile Fibres, Textile Weaving, Finishing of Textiles, Manufacture of Made-up Textile Articles, except Apparel	*171-174*
Other Textiles, Knitted and Crocheted Fabrics and Articles	*175-177*
Wearing Apparel; Dressing and Dyeing of Fur, Leather and Leather Products	*180-193*
Wood and Wood Products	*201-205*
Pulp, Paper and Paper Products	*211*
Articles of Paper and Paperboard, Reproduction of Recorded Media	*212*
Pulp, Paper and Paper Products, Publishing and Printing	*221-223*
Coke, Refined Petroleum Products and Nuclear Fuel	*231-233*
Basic Chemicals, Pesticides and Other Agro-chemical Products, Paints, Varnishes and Similar Coatings, Printing Ink and Mastics	*241-243*
Pharmaceuticals, Medicinal Chemicals and Botanical Products, Soap and Detergents, Cleaning and Polishing Preparations, Perfumes and Toilet Preparations, Other Chemical Products, Man-made Fibres	*244-247*
Rubber Products	*251*
Plastic Products	*252*
Glass and Glass Products	*261*
Non-refractory Ceramic Goods Other than for Construction Purposes; Refractory Ceramic Products, Ceramic Tiles and Flags, Bricks, Tiles and Construction Products, in Baked Clay	*262-264*
Cement, Lime and Plaster, Articles of Concrete, Plaster and Cement	*265-266*
Cutting, Shaping and Finishing of Ornamental and Building Stone, other Non-metallic Mineral Products	*267-268*
Basic Iron and Steel and of Ferro-alloys, Tubes, Other First Processing of Iron and Steel	*271-273*
Basic Precious and Non-ferrous Metals, Casting of Metals	*274-275*
Structural Metal Products	*281*
Tanks, Reservoirs and Containers of Metal; Manufacture of Central Heating Radiators and Boilers, Steam Generators, except Central Heating Hot Water Boilers, Forging, Pressing, Stamping and Roll Forming of Metal; Powder Metallurgy	*282-284*
Treatment and Coating of Metals; General Mechanical Engineering	*285*
Cutlery, Tools and General Hardware	*286*
Other Fabricated Metal Products	*287*
Machinery for the Production and use of Mechanical Power, except Aircraft, Vehicle and Cycle Engines	*290-291*
Other General Purpose Machinery, Weapons and Ammunition, Dom. Appliances nec.	*292, 296-297*
Agricultural and Forestry Machinery, Machinetools	*293-294*
Other Special Purpose Machinery	*295*
Office Machinery and Computers, Electric Motors, Generators and Transformers	*300, 311*
Electricity Distribution and Control Apparatus, Insulated Wire and Cable, Accumulators, Primary Cells and Primary Batteries	*312-314*
Lighting Equipment and Electric Lamps	*315*
Electrical Equipment n.e.c.	*316*
Radio, Television and Communication Equipment and Apparatus	*321-323*
Medical and Surgical Equipment and Orthopaedic Appliances	*331*
Instruments and Appliances for Measuring, Checking, Testing, Navigating and Other Purposes, except Industrial Process Control Equipment	*332*
Industrial Process Control Equipment, Optical Instruments and Photographic Equipment, Watches and Clocks	*333-335*
Motor Vehicles, Bodies (Coachwork) for Motor Vehicles; Trailers and Semi-trailers	*341-342*
Parts and Accessories for Motor Vehicles and their Engines	*343*
Other Transport Equipment	*351-355*
Furniture, Jewellery and Related Articles	*361-362*
Games and Toys, Miscellaneous Manufacturing n.e.c.	*365-366*