2011

Essays on Foreign Direct Investment, Trade and Development

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by

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A dissertation submitted to the Graduate Faculty in Economics in partial fulfilment of the requirements for the degree of Doctor of Philosophy, The City University of New York

2011

This manuscript has been read and accepted for the
Graduate Faculty in Economics in satisfaction of the
dissertation requirement for the degree of Doctor of Philosophy.

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ABSTRACT

ESSAYS ON FOREIGN DIRECT INVESTMENT, TRADE AND DEVELOPMENT

Advisor: Professor Robert Lipsey

Essay 1: Most of studies on developing countries have found evidence that international linkages, such as foreign ownership, exporting, or importing, affect productivity growth, but since these variables are correlated, it is hard to distinguish among their effects. This paper tackles this issue by explicitly investigating and comparing the productivity effects of all three international linkages at plant levels in case of Indonesian manufacturing plants during 1993-2001. Overall, the paper finds that foreign ownership, first, and importing, second, but exporting doubtfully, promoted productivity growth. Productivity jumps in the year when plants are acquired by foreigners or when plants first start to import, although the productivity effects from importing become smaller after two years following the initiation of imports. Methodologically, I first obtain a measure of plant productivity that corrects for the selection and simultaneity biases. Then I control for plant characteristics through matched sampling techniques to establish proper comparison sets between plants with and without international linkages. Thirdly I apply difference-in-differences model and plant-pair fixed-effects regressions on matched samples. The unobserved plant characteristics are effectively controlled this way.

Essay 2: Studies have shown that foreign direct investment (FDI) is the main driver for China's rapid export growth in recent decades. This paper asks how China's export growth is associated with the exports from its investing countries. I first examine and compare the evolution of the

export growth of China and its investing countries over time (1962-2006), and then assess the similarity between their present export bundles by trading partners and sectors. The results show that China's export content is increasingly similar to that of its investing countries, despite China's relatively low income levels. Lastly, I identify the impact of China's export growth on its investing countries' exports using gravity equation. The results show a complementary relationship between China's exports and its investing countries' exports.

Essay 3: Borrowed from the literature of program evaluation, the combination of difference-in-differences and propensity score matching is becoming popular in the literature of foreign direct investment (FDI). This study evaluates the extent to which the matching estimator is sensitive to the choice of matching methods in the study of foreign acquisition and compares the matching estimator with various panel data techniques widely used in the related literature that resolve the endogeneity issue. Using the panel data on Indonesian manufacturing establishments for 1975–2005, I find that the different matching methods produce similar estimates when the balancing property is satisfied. Furthermore, the estimates from the matching estimator are most similar to the fixed effects estimates and dynamic panel estimates.

ACKNOWLEDGEMENTS

Over my long journey of graduate study, numerous individuals have helped me to make this dissertation possible and make my study such an unforgettable experience. The list is long, but I cherish each contribution to my development as a researcher.

My greatest acknowledgement should go to my advisor, my boss, and my friend, Dr. Robert Lipsey. I know how lucky I am to get to know him, to work for him, and to work with him. It was him who gave me the opportunity to work at NBER, where I grew from a research assistant to an independent researcher. I highly appreciate how much time he devoted to reading my dissertation, giving insightful comments and useful suggestions in every phase of my dissertation. I know I cannot replicate his success, but he is my role model in research and in life.

I also run out of words to thank Dr. Wim Vijverberg for giving me so much help in finishing my dissertation. He gave up a lot of personal time including weekends to read and comment on various drafts of my dissertation. His comments have greatly improved the papers. His serious scholarship is what I aspire to as a young researcher.

I extend my gratitude to Dr. Zadia Feliciano for her kindness, support and help in all these years. She is the person who introduced me to the opportunity at NBER and who always has faith in me. Thanks for serving in my committee and all the help in my journey to the doctoral degree.

Special thanks to Dr. Michael Grossman for his support during my graduate study and his assistance in my job search. His great intellect, his readiness to help others, his devotion to his students… The list of things I learned from him goes long. Mike, you are the economist that I aspire to emulate.

I also wish to thank Dr. Thom Thurston and Dr. Merih Uctum. They did a great job as the chairman of the economics program. They are always ready to listen to the students and strived to find financial support to students, especially international students. I appreciate their help during my graduate study.

I will never forget Dr. Salih Neftci, although he can never read this acknowledgement. He is the person who has changed my thinking in many ways and who taught me how to survive in the world. He introduced me to the Economist and Financial Times, which I have subscribed to since 2005 and have opened my eyes to the world.

I want to express my gratitude to my co-author, Dr. Fredrik Sjöholm, for getting me involved in the Indonesian project. I learned so much from working on the project.

I would also want to thank NBER, which has made a difference to my life and to my view of the world. I was fortunate to have lunch with Dr. Anna Schwartz, Chris and Dr. Robert Lipsey almost every day. The conversations at lunch shaped my view in economics and fostered my belief in competitive market system. I also thank Chris and Marinella for their great support. I appreciate the encouragement from Dr. Rachael Boaz.

I am particularly thankful to all my friends at the economics program. They made my Ph.D. study much enjoyable.

Finally, and most importantly, I would like to express my gratitude to my family. I want to thank my parents and my brother for their unconditional love and for their faith in me in all these years. I cannot imagine my life without their support. I would also like to thank my husband Dr. Yangang Xi, whose unwavering support and quiet patience carried me through all these years. He taught me to be persevering and patient in face of ups and downs in life. I cannot

be here without him. I also want to thank my daughter, Anna Xi, for being a great angel and for giving me more motivation to finish my degree.

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Part I:

International Market Linkages and Productivity of Indonesian Manufacturing Plants

1.1 Introduction and Motivation

In the past two decades, many developing countries liberalized their trade and investment regimes, aspiring to acquire advanced technologies and improve productivity at home through more foreign contacts. Foreign contacts could be established through various channels, such as exporting, importing, and foreign ownership (FDI). Despite the seemingly general agreement among policy-makers regarding the productivity effects from foreign contacts, the empirical evidence from academic literature is mixed as to whether foreign contact boosts plant productivity. This paper empirically analyses the issue in the case of Indonesian manufacturing plants and asks two questions. One is whether plants with higher productivity self-select into establishing foreign contacts or there is a learning effect through foreign contacts. The second question is how productivity effects, if any, differ among the three channels of foreign contacts.

International markets are characterized by more uncertainty and complexities in comparison to domestic markets. Plants need to be more productive to be able to cope with the extra costs associated with international markets. Simultaneously, plants could gain efficiency through more interactions with their foreign counterparts. A large body of literature has documented the superior performance of foreign-owned, or exporting, or importing plants in case of various countries. However, the direction of causality remains unclear. There are two competing hypotheses in explaining the high efficiency of plants with foreign contacts: self-selection vs. learning-by-doing. Moreover, the various channels of foreign contacts are described to have different partnerships between the domestic plants and their foreign counterparts, resulting in different impacts on plant productivity levels. Foreign ownership involves more monitoring from foreign counterparts[1] and is associated with a more direct and stable cooperation between the recipient and investing counterparts. In contrast, exporting and importing establish more dynamic relationships between the trading partners[2]. Exporting promotes technology transfer through sharing knowledge of the latest design and production technique (Blalock and Gertler 2004), while importing encourages imitation and adoption through the technology embodied in the intermediate and capital imports. Answers to these two questions have important implications for policy-making, especially in developing countries. If there is a learning effect in a particular sector or from a particular channel of foreign contacts, governments would probably want to subsidize the learning sector or the form of foreign contact that encourages more technology transfer.

Much of existing literature focuses on the productivity effects through one channel of foreign contact. This research fills a gap by considering all three channels together using the rich establishment data of Indonesian manufacturing plants. Methodologically, I first obtain a measure of plant productivity that corrects for selection and simultaneity biases. Then I control for plant characteristics through matched sampling techniques to establish proper comparison sets between plants with and without international linkages. Thirdly I apply difference-in-differences model and plant-pair fixed-effects regressions on matched samples. The unobserved plant characteristics are effectively controlled in this way.

This paper makes several contributions to the literature. First, it contributes to the discussion of self-selection vs. learning effects through foreign contacts by explicitly considering all three channels of foreign contacts. Most of the work, with the exception of a series of papers

[1] Grossman and Helpman (2004) concluded that FDI suffers the disadvantage of lesser monitoring compared with in-house production near the headquarters. But they also explained that a principal who operates a vertically-integrated firm may be better able to monitor her partner than the one who deals at arm’s length.

[2] Bernard and Jensen (1999) and Aw, Chung and Roberts (2000) made use of the dynamics of exporting to study the productivity effects of the entry and exit of export market.

by Yasar and Paul (2007 and 2008)[3], focuses on one channel. Emphasis on one channel could produce misleading conclusions as different ways of foreign contacts are likely to occur together (Kraay et al, 2002). The exclusion of other channels of foreign contact could result in omitted variable bias picking up productivity effects from other unidentified channels. The second contribution of the paper is the procedure for appropriately controlling the observed plant characteristics through matched sampling. The empirical research has consistently shown that plants with and without foreign contacts differ substantially from each other in many characteristics such employment, productivity, etc. An additive regression equation applied to the entire sample essentially controls covariates by forcing the same linear relationship on plants with and without foreign contacts. Matching methods have been shown to reduce these confounding variable biases (Rosenbaum and Rubin 1984; Heckman et al. 1997) by balancing the relevant pre-foreign-contact plant characteristics for plants with some foreign contacts later and those never making foreign contacts. The last contribution is the combination of propensity score matching with model-based regression adjustments. Although an extensive list of plant characteristics have been matched, biases may still exist due to many unobserved covariates or incomplete controls. Rubin and Thomas (2000) illustrates that combining propensity score matching with regression adjustment effectively reduces the biases. To my best knowledge, this approach has not been applied to the literature on productivity and foreign contacts.

The main findings of this study are that foreign ownership and importing improve productivity, while exporting does not. In other words, plants with higher productivity self-select

[3] Yasar and Paul (2007 and 2008) used Turkish manufacturing data to assess the productivity effects of all the three channels of foreign contacts and found that all of the three channels boost productivity. Yasar and Paul (2007) studied this question with quantile regression techniques emphasizing different productivity relationships for different size plants. Yasar and Paul (2008) used propensity score matching to study productivity effects of foreign contacts. This paper studies the same question with the matched sampling technique. Yasar and Paul (2008) applied the average treatment effects model on the matched samples while this paper uses the difference-in-differences model and model-based regressions on the matched samples. More discussions on the methodologies are in Section 1.4.

into export market, but there are learning effects through foreign ownership and importing. The productivity effects are more closely related to foreign ownership. Foreign ownership increases plant productivity by 23 percent on average after foreign acquisition, while importing enhances plant productivity by approximately 9 percent. Productivity jumps in the year when plants are acquired by foreigners or when plants first start to import, although the productivity effects from importing become much smaller after two years following the initiation of imports.

The rest of the paper is organized as follows. Section 1.2 provides an overview of the empirical issues and reviews previous work in this area. Section 1.3 looks at data and summary statistics. Section 1.4 introduces the empirical estimation strategy. Section 1.5 discusses the estimation results. Section 1.6 concludes.

1.2 Previous Studies and Empirical Issues

There is no consensus about whether plants with higher productivity self-select into establishing foreign contacts or there is a learning effect through foreign contacts. More productive firms could self-select into establishing foreign contacts because their superior characteristics make them able to deal with the costs and complexities of international markets. On the other hand, the establishment of foreign contacts could enhance productivity through learning effects as domestic plants could gain exposure to state-of-the-art technology and managerial skills from their international clients and competitors. Most of the studies focus on one channel of foreign contacts and sometimes control one other channel as a robustness check.

Exporting firms or plants are documented to have systematically superior characteristics compared to their domestic counterparts. Exporters are normally bigger, more productive, more capital intensive, and pay higher wages (Bernard and Jensen 1995). However, it is not clear whether there is a causal linkage between exporting and productivity. Evidence supports both sides of the argument. For example, Bernard and Jensen (1999) used US census data and found that high-productivity firms become exporters but the benefits of exporting for firms are less clear. Clerides et al (1998) developed a maximum likelihood approach to analyze the causality between exporting and plant efficiency in three developing countries and found evidence of self-selection. Delgado et al (2002) employed a nonparametric approach on Spanish firms and their results also showed that better plants self-select into export market. In contrast, Van Biesebroeck (2005), using a panel of manufacturing firms in nine African countries, demonstrated that exporters increase their productivity advantages after entry into export market. A study on Indonesia during the period of 1990 to 1996 by Blalock and Gertler (2004) showed that firms experience a jump in productivity following the initiation of exporting. To sum up, it is far from consensus whether the higher productivity of exporters comes from self-selection or learning-by-exporting.

Importing could boost productivity via learning, variety, and quality effects and importing new technologies is a more direct source of productivity growth. Halpern et al. (2005) used a panel of Hungarian firms during 1992-2001 to examine two different channels of productivity improvements, a quality and a variety channel, and found that importing inputs increase aggregate total factor productivity by 30 percent. However, analogous to the entry cost into export market (Melitz 2003), there is a sunk cost for entry into importing. Thus it is likely that only plants or firms with higher productivity could afford the cost to find international suppliers, confounding the possible learning effects from importing. There is empirical evidence on both sides of the argument. Kasahara and Rodrigue (2008) provided evidence that becoming an importer of foreign intermediates improves productivity in case of Chile. In contrast, Muendler (2004) showed that the use of foreign materials and investment goods plays a minor role in productivity change in Brazil during 1986-1998. A related study by Amiti and Konings (2007) on Indonesia found that input tariff reduction leads to improved productivity for importing plants, though this does not necessarily imply that importing by itself would improve productivity. Another study on Indonesia by Takii (2004) studied the plant efficiency in the automotive industry and finds that imports from ASEAN region have positively affected the productivity of domestic and foreign-owned plants.

A large body of literature has shown that foreign-owned plants/firms enjoy a higher level of productivity compared to their domestic counterparts. Lipsey (2004) and Lipsey and Sjöholm (2005) provided excellent surveys on this issue. However, it is not immediately obvious whether firms/plants with higher productivity are more likely to be taken over by foreigners, so-called “cherry-picking” in the related literature on FDI or “self-selection” in the literature on exporting or importing, or whether firms/plants could improve productivity by learning the state-of-art technologies and by acquiring international market knowledge through their partnership with foreign counterparts. Much of the literature on productivity and foreign ownership is at industry-level and has been directed at the question of whether there were vertical/horizontal spillovers to domestic firms rather than within plant productivity improvement (Javorcik and Spatareanu 2009, Blalock and Gertler 2008, Blomström and Sjöholm 1999, Aitken and Harrison 1999). The only exception is Arnold and Javorcik (2009), which found that foreign acquisition could improve within-plant productivity. Similarly, this paper fills the gap by looking at the within-plant productivity improvement.

More recently, some studies have approached this topic by combining some or all channels of international linkages. Seker (2009) used a detailed firm level dataset from 43 developing countries and investigated the productivity effects from exporting and importing channels. He found that estimating export premium without controlling for import status is likely to overestimate the actual value by capturing the import premium. A series of papers by Yasar and Paul (2007, 2008) on several Turkish industries considered all the three channels together and provide evidence that productivity is mostly closely related to foreign ownership, followed by exporting.

Methodologically, most of the literature on international market linkages and productivity involves two steps. First, productivity is estimated using index numbers or is estimated econometrically using production functions. Subsequently, productivity estimates are regressed on a set of dummy variables characterizing the dynamics of a plant’s foreign contacts. This approach has been adopted mainly in the studies of exporting and productivity such as Bernard and Jensen (1999) and Aw et al (2000). This paper uses a similar methodology in the sense that the estimated productivity are regressed on a set of dummy variables describing the dynamics of a plant’s foreign contacts, though the estimation of productivity and the estimated samples are obtained differently, as will be discussed in more detail in the following sections. The index number productivity measure has the advantage that no estimation is required, but as Van Biesebroeck (2003, 2004) illustrated, the index number measure is less robust to the measurement error than econometric productivity estimates.

A number of studies obtain the productivity measure by estimating a production function and the productivity effects of an international linkage is estimated by including a dummy variable indicating the linkage (such as exporting) in the estimation of production functions. The estimated coefficient on the linkage dummy variable is taken as the productivity effects of this particular channel. For example, Van Biesebroeck (2005) and Blalock et al (2004) adopted this approach for the exporting channel, Halpern et al. (2005) and Kasahara et al (2008) for the importing channel, Yasar and Paul (2007) for all three channels together. Although this approach improves the productivity measures, it does not control for plant characteristics other than those included in the estimation of production function. Most of the studies above have documented that plants with international linkages are systematically different from their domestic counterparts. Without controlling for plant-specific characteristics, the results could pick up effects from other unidentified factors.

1.3 Data and Preliminary Results

Indonesia provides an interesting setting for the research on productivity effects of international linkages. It is a large developing country with great economic achievement through economic liberalization in the past two decades and it provides rich micro datasets. The main data source is the Manufacturing Survey of Large and Medium-sized Firms (Survei Industri, SI) in Indonesia from 1993 to 2001. The data are from an annual survey of manufacturing establishments with more than 20 employees. This survey provides a wide range of variables including ownership, exports, imports, outputs, inputs, etc. Industry wholesale price indices (WPI) are used to deflate plant-level output. These are published in the Monthly Statistical Bulletin of Economic Indicators (see the appendix for details on deflators).

The production function is estimated by using the information on output and three factors of production: the number of workers, materials and capital. The capital stock is measured by the replacement value of fixed assets with the year 1996 missing. I interpolated the capital stock for the year 1996 using the 1997 and 1995 values. Since the data contain no information on physical quantities of inputs used or output produced by plants, I have to deflate the nominal values using a set of wholesale price indices for manufactured commodities as discussed in Section 1.4.1 (Details are also available in the appendix.).

The data have been cleaned to remove large unrealistic numbers and estimate some missing values. The cleaning process is described in the appendix. In the end, the sample has an unbalanced panel of approximately 22,000 plants in total and more than 15,000 plants per year. The first panel of Table 1.1 gives the summary statistics for the variables used for estimating productivity. Section 1.4.1 discusses the details of estimating productivity at industry levels. The second panel of Table 1.1 presents the plant characteristics by international linkages. Consistent with findings from the related literature, plants with any foreign contact in general hire more employees and more white-collar workers, and are more capital-intensive, compared to the plants with no foreign contacts at all. However, for plants with international linkages, the average descriptive statistics could not reflect the causal relationship between foreign contacts and their superior plant characteristics since it is not clear whether plants possess these characteristics before or after they set up the new foreign contact. The conclusion is that plants with foreign contacts are systematically different from those without foreign contacts. As a matter of fact, it is the distinctive characteristics of the plants with foreign contacts that encourage governments to provide incentives to home business to set up foreign contacts. Thus, it is crucial to identify the causality between the foreign contacts and plant productivity.

I then characterize each plant in terms of the dynamics of its international linkages. Plants are grouped into four groups: during the sample period, plants that do not have any foreign contact, plants that do not export initially but enter the export market later, plants that do not import initially but enter the import market later, and the plants that do not have foreign ownership initially but are acquired by foreign investors. Over the sample period of 1993-2001, out of more than 22,000 plants, 78 percent of them do not have any foreign contacts. These later provide a vast pool for selecting the control plants. About 14 percent of the total plants enter the export market, more than 7 percent enter the import market, and only 0.7 percent are acquired by foreign investors. Table 1.2 gives the industry distribution of the plants by the dynamics of its international linkages along with the mean characteristics at industry levels defined at the three-digit level of ISIC. The international linkages of plants vary greatly across industries. Foreign acquisition is a rare phenomenon, making it infeasible to do industry level regression analysis later. Log capital per worker and log of raw materials per worker show similar means across different industries, whereas both the employment and the ratio of white-collar workers vary across industries.

There are plants that establish some foreign contact for one year, and then either exit the foreign relationship or set up multiple channels of foreign contacts within two years. In the regression analysis, I drop these plants and study only the plants that establish one channel of foreign contact and stay so within three years. There are two reasons for the selection. First, the entry into and the exit of foreign market within two years could be trial orders or typos, which should not have significant impact on the productivity. Second, although the study of multiple channels could be intriguing, the lack of observations following similar pattern of setting up foreign contacts make it hard to carry out regression analysis[4].

1.4 Estimation Strategy

[4] An attempt has been made to carry out the analysis with multiple channels. For example, to study the productivity effects of foreign ownership on exporting plants, plants that are exporting first and then acquired by foreign investors could be compared with plants that are always exporting. There are only 39 plants following the same pattern in the year of foreign acquisition, 16 plants remain exporting and foreign-owned in the next year, and even much less plants available in the subsequent years. As a result, the sample size does not allow such study in most cases.

1.4.1 Productivity

To determine the productivity effects of foreign contacts, I consider a plant with a Cobb-Douglas production function:

$$\begin{aligned} y_{it} &= \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + e_{it} \\ e_{it} &= \omega_{it} + \mu_{it} \end{aligned} \tag{1.1}$$

where y_{it}, l_{it}, m_{it}, k_{it} are gross output, labor, materials, and capital used by plant i at time t. All the variables are in logarithms so that the coefficients on inputs are interpreted as elasticities. The plant specific term, e_{it}, is a function of a plant-specific efficiency, ω_{it}, known by the plant but not by the econometrician, and an unexpected productivity shock μ_{it}. In this framework, any plant-level productivity measure relies on the difference between a plant's actual output and the predicted output. Thus it is crucial to obtain consistent estimates of the coefficients on input variables in the production function. However, as the unobservable productivity shock, ω_{it}, is known to the plants, it could affect the plants' choice of input levels, resulting in simultaneity biases. OLS estimates yield inconsistent estimates in this situation. The input variables are likely to be correlated positively with the error term. This results in an upward bias of the coefficients on the input variables, like labor and material, under OLS.

The semi-parametric estimator originally proposed by Olley and Pakes (1996) overcomes the simultaneity biases in the estimation of production function and controls for endogenous exit from the sample, which is assumed to occur when productivity falls below a threshold. In particular, Olley and Pakes (1996) argue that plants with more capital, such as plants with foreign contacts, are likely to weather greater reductions in productivity, making the exit threshold a decreasing function of capital. The underlying approach uses the investment as a proxy for these unobservable productivity shocks. The investment function, $i_t = I_t(k_t, \omega_t)$, is assumed to be monotonically increasing in productivity (ω_t) for any given level of capital. Inverting the investment function gives an expression for productivity as a function of capital and investment:

$$\omega_{it} = I_t^{-1}(i_t, k_t) = \theta_t(i_t, k_t) \qquad (1.2)$$

Substituting productivity function (eq. 2) into production function (eq. 1) allows estimation of the input coefficients using nonparametric techniques. In the first step, the coefficients on labor and materials are recovered using nonparametric techniques, controlling for the dependency on investment and capital. In the second step, the plant's probability of staying in the market is obtained using a probit regression. In the third step, the coefficient on the state variable, capital, is recovered through semiparametric nonlinear least squares estimator.

For current application, I modify the Olley-Pakes approach to take into account more state variables in addition to capital, such as three channels of foreign contacts. The plants' decision to establish foreign contacts may have an impact on the evolution of productivity. Through any of the three channels, plants are brought into close contact with foreign partners, which may lead to positive externalities, or "learning through foreign contacts[5]. Plants with foreign contacts might choose a different investment level and have a different exit rule, even controlling for capital stock and productivity, because they face different factor markets and different market prospects. Hence, the investment function becomes $i_t = I_t(k_t, \omega_t, EXP_t, IMP_t, FDI_t)$ and the inverse productivity function becomes

[5]Kasahara and Rodrigue (2008) provide a detailed derivation justifying importing as a state variable in obtaining productivity. Importing could have an impact on productivity through variety, quality and learning effects. Similar extensions have been developed in more detail by Van Biesebroeck (2005) in the context of firms that export. Lipsey (2004) summarizes a host of literature on the productivity advantages by foreign-owned plants, which implies the effects of foreign ownership on productivity.

$\omega_{it} = I_t^{-1}(i_t, k_t, EXP_t, IMP_t, FDI_t) = \theta_t(i_t, k_t, EXP_t, IMP_t, FDI_t)$. Plug it into the production function (eq. 1) gives a partial linear model:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \theta_{it}(i_{it}, k_{it}, EXP_{it}, IMP_{it}, FDI_{it}) + \mu_{it}$$

The estimation algorithm is the same as before. I use a series estimator with a fourth-order polynomial in investment, capital, and three channels of foreign contacts to obtain the consistent estimates of input coefficients on labor and capital in the first step. The subsequent steps are conducted similarly with the addition of channels of foreign contacts.

Using the estimates of the input coefficients from the Olley-Pakes methodology[6], the log of productivity of plant i at time t, denoted by pr_{it}, as

$$pr_{it} = y_{it} - \hat{\beta}_0 - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it} - \hat{\beta}_k k_{it} \qquad (1.3)$$

The dependent variable is total revenue deflated by five-digit industry level producer price indices. Nominal material values are deflated using the wholesale price indices for the nearest corresponding commodity at four-digit ISIC level. The capital price deflator is obtained by weighing the aggregate price index of imported electrical and nonelectrical machinery and equipment, imported transport goods, and the wholesale price index of manufactured construction materials. Details on deflators are available in the appendix.

It is important to take account of all the channels in estimating productivity since each of them could have its own way to affect input choices and the omission could result in biased estimates of input coefficients. Now the estimated plant-level productivity is a function of foreign contacts and further analysis on the relationship between productivity and foreign

[6] Levinsohn and Petrin (2003) put forward a similar procedure to obtain a measure of productivity. The idea is that investment data are not always available and thus raw materials or electricity consumption could serve as the proxy variable. However, the dataset used in this research has the same number of observations missing in raw materials, electricity consumption, and investment. Olley-Pakes productivity measure controls for the endogenous exit and thus is adopted here.

contacts could be carried out. I estimate productivity at plant levels for each group of plants that operate in the same sector, defined at the three-digit level of ISIC. In order to verify that the results are not driven by the methodology of estimating productivity, in the following estimation I use labor productivity, proxied by value added per employee, as a robustness check[7].

The estimated input coefficients are reported in Table 1.3. The OLS estimates are included for comparison. Since OLS does not adjust the positive correlation between input choice and the productivity shocks known to the plants, the labor and material coefficients are overestimated with OLS. However, it is ambiguous as to the direction of bias from OLS estimates of the capital coefficients. If more productive plants are more likely to invest more in capital, then OLS gives a higher estimate of capital coefficient. But if firms with larger capital stocks can continue in operation at lower ω_t realizations, then the exit is endogenous of capital stocks. This implies that, productivity shock, ω_t, conditional on the surviving plants is a decreasing function of capital, yielding a downward bias on the coefficient on capital (Olley and Pakes 1996). The results in Table 1.3 show that almost all the OLS estimates of the input coefficients are larger than the Olley-Pakes estimates.

Table 1.4 compares the productivity of the plants with different international linkages. International linkages are constructed to indicate plants with one channel of foreign contact only. For example, foreign ownership refers to the plants that are foreign-owned only, but neither export nor import. The total factor productivity measure (Olley-Pakes) and the labor productivity, reveal similar conclusion about the distribution of productivity across different international

[7] The Tornqvist index is another measure of productivity that could be used for robustness check. Aw et al (2000) used this index as a measure of productivity. However, to obtain the Tornqvist index requires factor price information and returns to scale. The wage information in the data used in this paper is not reliable. This index is sensitive to measurement error or outliers and thus is not used. Van Biesebroeck (2008) experimented five measures of productivity including both Olley-Pakes and the index numbers. He found that different measures of productivity yield surprisingly similar results.

linkages. Plants with any foreign contact have higher productivity compared to those with no foreign contacts at all.

The above estimation does not restrict returns to scale. Plants with different international linkages could display different scale economies, which is closely associated with the productivity effects from international linkages. For this purpose, I perform Olley-Pakes estimation on plants with different type of international linkages. Table 1.5 tabulates the results. The scale economies are estimated to be close to unity across different channels of foreign contact. Importing plants have slight increasing returns to scale, while the exporting plants have modest decreasing returns to scale.

1.4.2 Matched Sampling

After obtaining the measure of productivity, the next step should be to relate productivity to international linkages to find the causal relationship. However, the regression on this sample imposes the same linear relationship between plants with and without international linkages on the plant characteristics controlled, although plants with and without international linkages are systematically different. In other words, the linear regression on such a sample could result in an extended extrapolation across plants since plants without foreign contacts have distinctive characteristics from those with foreign contacts and are weighted equally in linear regression. Matched sampling is used to resolve this issue. Matched sampling is a method for selecting units from a large pool of potential controls of a reduced control group that has similar distributions of observed covariates to a treated group (Rosenbaum and Rubin 1985). In this research, the analogue for treatment is the establishment of some foreign contact, and the control group includes the plants without any foreign contact. By balancing the relevant pre-foreign-contact plant characteristics for plants with and without foreign contacts, matching methods have been shown to reduce these confounding variable biases (Rosenbaum & Rubin 1984; Heckman et al. 1997).

Matching based on one specific variable would only balance one characteristic between plants with and without foreign contacts, but this does not help to eliminate biases due to disparities in other plant characteristics. The challenge is to find a composite score that encompasses all the plant characteristics that are deemed to be important both for the probability of establishing foreign contacts and for improving productivity at plant levels. Rosenbaum and Rubin (1983) proposed the use of propensity scores to resolve the dimensionality problem of matching all the plants' characteristics. More specifically, the propensity score collapses a vector of plant characteristics into a composite score based on observables, representing the plant's probability of establishing foreign contacts. Then the composite score obtained could be used to match the plants with and without foreign contact using a number of matching methods including nearest neighbor matching.

In this research I construct a matched sample for each channel of foreign contact. The control group is created from the vast pool of plants that never have any foreign contacts, while the treated group is from plants that have only one channel of foreign contact for at least two years after the foreign contact is firstly set up. The matched pairs are obtained by using a logit model and through the nearest neighbor matching. The nearest neighbor matching has the advantage of finding for each plant with foreign contact a match from the plants without foreign contact but sharing similar plant characteristics. I imposed the constraint that the treated units and the matched control units should be in the same year[8] and same industry. As a result, for

[8] Relaxing the same-year requirement would increase the potential control units that could be chosen from. The accuracy of the matched pairs could potentially be improve, but the size of the matched sample would not increase

some treated plants with foreign contact, it is unlikely to find a matched control plants without foreign contact. In either matched samples, the important diagnostic check for the effectiveness of the matching is the covariate balance within matched pairs (Rosenbaum & Rubin 1984). I apply the standardized differences (SDiff) and t-test to check the similarity of covariates distributions within the matched samples. In the standardized differences test, for each covariate, I take the average difference between the treated units and the matched control units and normalize it by the pooled standard deviation of the covariate in the treated and control samples. The following measure, based on Rosenbaum and Rubin (1985), is calculated:

$$SDiff\left(X_k\right) = 100\frac{\frac{1}{n_t}\sum_{i\in t} X_{ki} - \frac{1}{n_c}\sum_{j\in c} X_{kj}}{\sqrt{\frac{Var_{i\in t}\left(X_{ki}\right) + Var_{j\in c}\left(X_{kj}\right)}{2}}} \tag{1.4}$$

where n_t is the number of plants with some foreign contact and n_c is the number of matched control plants. The drawback of this test is that, as noted in Smith and Todd (2005), there is no clear criterion for determining if a value of the standardized difference is too large. Rosenbaum and Rubin (1985) suggest that a value of 20 is large. The results of the test are presented in the results section.

1.4.3 Difference-in-differences (DD) and Regression Models

Through matched sampling, now the sample has plant pairs, each of which has similar plant characteristics before one of them either enters the international market or is acquired by foreign investors. Still there could be potential biases from the disparities between treatment and

since one plant with foreign contact is mapped to only one plant without foreign contact. Additionally, t-test and standardized tests are used to check the similarity between the plants with and without foreign contact. Moreover, it is important to have both plants with and without foreign contact from the same year in Indonesia since the Asian financial crisis in 1998 could have an impact on the productivity effects.

control group due to unobserved variables that are not controlled for. To further uncover the relationship between productivity and foreign contact, I apply difference-in-differences (DD) model and plant-pair fixed effects model on the matched samples. First, assuming that the unobservable is time-constant, the DD estimator removes the bias by comparing productivity before and after foreign contacts. Second, potential biases from incomplete controls are addressed by using a panel data regression method (Rubin and Thomas, 2000). The formal regression models are estimated for each channel on the matched pairs.

In particular, the DD estimator is obtained in the following way:

$$DD_n = E\left(pr_{1,t'+n} - pr_{1,t'} \middle| X\right) - E\left(pr_{0,t'+n} - pr_{0,t'} \middle| X\right) \qquad n = 1, 2, 3 \tag{1.5}$$

Where t' is one time period before establishing foreign contact and n is the number of years since. DD_n represents the DD estimate of the productivity effect in n years since t'. For instance, DD_1 is the productivity effect in the year of establishing foreign contact. $pr_{1,t'+n}$ represents the productivity of plants with foreign contact n years since t', and $pr_{0,t'}$ represents the productivity of the matched control plant that actually does not have foreign contact at t'. This framework relies on the assumption that conditional on observables X, the potential unobserved bias stays the same over different time periods before and after foreign contact. Therefore, differencing the differences between the plants with and without foreign contact eliminates the bias. Applying this estimator on the matched sample is effective in reducing the bias (Heckman et al. 1997). During the years after foreign contact, productivity effects could start in the year of treatment especially in the case of foreign ownership (Arnold and Javorcik 2009). In this research, I start with the year of establishing foreign contact and focus on productivity effects within two years of setting up foreign contact.

Furthermore, I apply the regression model with pairwise fixed effects on the matched samples for each individual channel. For the sake of comparison, OLS is used on the unmatched sample with consideration of only one channel, regardless of the status of the other channels. On the matched sample, the formal regression models are estimated for different channels respectively. To estimate the average productivity effects of foreign contact in the years after establishing foreign contact, the following model is estimated:

$$pr_{i,j,t} = \beta_{0,i} + \beta_1 \times CONTACT_{i,j,t} + \beta_2 \times COVARIATES_{i,j,t} + \varepsilon_{i,j,t}$$

$$t = t' + 1, t' + 2, t' + 3 \qquad (1.6)$$

Where $pr_{i,j,t}$ is the productivity of plant j in matched pair i in year t, which could be the year of foreign contact ($t' + 1$), one year after foreign contact ($t' + 2$), and two years after foreign contact ($t' + 3$). $\beta_{0,i}$ is the pair-specific effects, which allows for heterogeneity across pairs. $CONTACT_{i,j,t}$ indicates the status of foreign contact of plant j of matched pair i in year t. $COVARIATES_{i,j,t}$ controls for a vector of control variables for plant j of matched pair i in year t including age, employment, proportion of white-collar workers, capital intensity, and use of raw materials.

The DD model allows for the analysis of the trajectory of productivity changes after foreign contacts. A similar analysis is carried in the regression framework. By defining different number of years forward as the post-foreign-contact period, the path of productivity growth could be tracked. Productivity effects could start from the year when foreign contact is established. Arnold and Javorcik (2009) document this pattern in case of foreign ownership. Specifically, the following regression model is employed to study this question:

$$pr_{i,j,t'+n} = \beta_{0,i} + \beta_1 \times CONTACT_{i,j} + \beta_2 \times pr_{i,j,t'} + \beta_3 \times COVARIATES_{i,j,t'} + \varepsilon_{i,j,t'+n} \qquad (1.7)$$

$pr_{i,j,t'+n}$ is the productivity of each plant j of pair i in the reduced sample in year $t'+n$ (n years after foreign contact). $\beta_{0,i}$ captures the pair-specific effects. $pr_{i,j,t'}$ is the productivity of each plant j of pair i in the matched sample in the matched year t' (one year before the foreign contact for plants with foreign contact, and the corresponding matched year for plants without foreign contact). $CONTACT_{i,j}$ is the dummy variable defined to show whether plants has foreign contact after the matched year. $COVARIATES_{i,j,t'}$ controls for the same vector of plant characteristics as above, albeit in the year before establishing foreign contact.

1.5 Results

1.5.1 Matched Samples

A logit model is used to fit the three channels of foreign contacts individually. Therefore, three samples are constructed. Each sample contains only plants with no foreign contacts at all and plants with only one channel of foreign contact. In the sample matching, the variables used for obtaining propensity scores include age, employment, employment squared, the proportion of white-collar workers, capital intensity, raw materials per employee, and the total factor productivity (Olley-Pakes measure in equation (3)) in year t', one time period prior to foreign contact. Except for age and proportion of white-collar workers, all the variables are in logs. Most of empirical studies find negative effects of age on the probabilities of establishing foreign contacts as older plants tend to have more bureaucracies making it harder to have foreign contacts. Employment is used to control the size of the plants and squared employment in the model allows for the nonlinear effects of employment on the probabilities of foreign contacts. The ratio of white-collar workers captures the structure of labor force at a plant level. Other variables are used to proxy the production technology and industry characteristics of the plants. This study uses the plant information in t', one time period prior to foreign contact, to obtain the propensity scores, though using earlier information would not change the results.

The results from fitting logit models are shown in Table 1.6. Age is negatively related to the probabilities of establishing foreign contacts, while all the other control variables are positively related, indicating that the plants with foreign contacts are systematically different from their corresponding control units. Productivity at one period before is related to the probability of establishing foreign contact and the possible productivity effects from foreign contacts. Takii (2005) documents that the technology gap is important in determining productivity effects from FDI. In the logit model, it is used to control the selection bias.

Next I carry out the nearest neighbor matching with replacement to match the plants with and without foreign contact based on the propensity scores obtained above. I explicitly control the matched plants without foreign contact coming from the same year and same industry as the plants with foreign contact. To assess how balanced this matched sample is, I conducted two balancing tests for all the control variables in the logit model. Table 1.7 to Table 1.9 provide the balancing results for three different matched samples matching each channel of foreign contact with plants having no foreign contacts. Comparing the SDiff and t-statistics of the covariates in the matched and unmatched samples, it can be clearly seen that the covariates are much balanced after matching.

For the purpose of comparison, I constructed two sets of samples. The first set of samples is matched samples for each single channel of foreign contact, in which the plants with foreign contact have only one channel of foreign contact. For example, plants are foreign-owned only but are neither exporting nor importing. The second set of samples is unmatched samples, in which each channel of foreign contact is defined without consideration of other channels. Formal regression models are carried on both samples for comparison.

1.5.2 Productivity Effects Following Foreign Contact

Matched samples adjust for the observed plant characteristics between treated and control plants before treatment (foreign contact). However, there are still unobserved factors that could contribute to the productivity changes that have not been accounted for. To further reduce the possible bias, I then apply difference-in-differences (DD) model and panel data regression on the matched samples.

Table 1.10 gives the results from applying DD model on the matched samples. By varying different after-foreign-contact periods, I track the productivity changes following foreign contact. The estimates show that both foreign ownership and importing improve plant productivity, but exporting does not. Productivity soars by approximately 43 percent (since $\exp(0.357) - 1 = 0.43$) in the year of foreign acquisition, and remains at a higher level in the two years after, though the estimated effects are not statistically significant in the following two years. Similarly, productivity jumps in the year when plants first start to import, but the productivity premia diminish in the following two years. The productivity effects from exporting, if any, are negative, though they are not significant. When labor productivity is used, foreign ownership and importing still play a positive role in improving productivity, but the timing pattern is different.

The DD model can only remove the time-constant unobserved factors. By using panel data regression on the matched samples, biases are further reduced. Table 1.11 presents the results from using plant-pair fixed effects model on both matched and unmatched samples. The estimates show that foreign ownership appears to have positive effects on productivity. Compared to plants with no foreign contacts at all, foreign-owned plants enjoy the highest productivity growth, and have productivity, on average, that is approximately 23 percent (since $\exp(0.204) - 1 = 0.23$) higher after foreign contact; exporting increases plant productivity by a meager 3 percent (since $\exp(0.025) - 1 = 0.23$) and it is not significant; importing, by contrast, boosts plant productivity by almost 9 percent (since $\exp(0.083) - 1 = 0.09$). All the control variables have the expected signs. In case of productivity and foreign ownership, this is similar to findings in Arnold and Javorcik (2009). They found that the productivity of foreign-owned plants increased by approximately 15 percent in the year of foreign acquisition, though their results are based on the definition of foreign ownership without consideration of other channels. As far as the relationship between productivity and exporting is concerned, the results are similar to Bernard and Jensen (1999), lending support to self-selection hypothesis. By contrast, the results from unmatched samples, using the same model specification, yield different conclusions. All three channels of foreign contacts increase plant productivity, though at a different scale, and they are all statistically significant. Among them, foreign-owned plants still have the highest productivity premia, followed by importing. The productivity effects from foreign ownership are robust whether it is matched sample or not, while the productivity effects from importing are smaller than those estimated from the matched sample. This shows the possible bias arising from omitting other channels of foreign contact. In addition, more coefficients on the control variables are significant, indicating an extended extrapolation of OLS due to the considerably large difference in many characteristics between plants with and without foreign contacts and due to the vast pool of plants without any foreign contact at all.

1.5.3 Trajectory of Productivity Changes after Foreign Contact

The estimates from the DD model reveal that productivity changes from foreign contacts have different path before and after foreign contacts. Figure 1.1 to Figure 1.3 illustrates the trajectory of productivity growth for each channel of foreign contact in matched samples. In any case, productivity increases in the two years after foreign contact. However, compared to the productivity growth of plants with no foreign contacts but sharing similar characteristics, the increase in productivity for foreign ownership and importing is more evident in the year of foreign contact, although it becomes less obvious in the subsequent years after foreign contact in case of importing. The control group for exporting plants has experienced similar productivity growth, which may explain why exporting does not significantly promote productivity in the above analysis.

Additionally, Figure 1.1 to Figure 1.3 also shows that, in the one period before foreign contact ($t = -1$), the matched plants without foreign contact have different initial levels of productivity. The control plants matched to the plants with foreign ownership have the highest initial level of productivity, the ones matched to the exporting plants have the second high level of productivity, and the ones matched to the importing plants have the least level of productivity. This suggests the sample selection of plants into different channels of foreign contact, which could have an impact on the learning effects after foreign contact.

Next I use a formal regression model to study how productivity changes following foreign contact. The regression models are specified in Section 1.4.3. Specifically, the year of foreign contact, one year forward, and two years forward are specified. The errors in all the equations have been corrected for heteroskedasticity at plant levels. Table 1.12 demonstrates that compared to plants with no foreign contacts at all, foreign ownership boosts productivity starting from the year of foreign acquisition and remains so until two years afterward. In the year of foreign acquisition, the productivity of plants that are acquired by foreigners are 40 percentage points (since $\exp(0.333) - 1 = 0.40$) higher than their matched plants without foreign ownership, after controlling the productivity differentials one period before. The productivity advantages of foreign-owned plants increased to 52 percentage points (since $\exp(0.417) - 1 = 0.52$) higher two years after foreign acquisition. In addition, although exporting does not have significant productivity effects in the year when plants first start to export, exporting increases productivity two years after exporting. If the analysis could be carried out in a longer time span, exporting might have a positive impact on productivity in later years. However, the research is limited by the data availability since the number of plants that enter export market and stay only in the export market for three years after entering decreases greatly, and thus I have to focus on two years after exporting. The average productivity effects from exporting in the study period are positive but not statistically significant. By contrast, the productivity effects from importing are evident in the year when plants start to import. However, the effects become smaller and insignificant afterward. These findings are consistent with those from DD model. Considering the initial difference in productivity levels among different channels, the productivity effects from foreign ownership is genuinely high, while the plants entering the export market do not enjoy an immediate boost in productivity growth possible due to the fact that they normally have higher initial levels of productivity comparing to those entering the import market.

As a robustness check, Table 1.13 gives the results when labor productivity is employed using the same model specification. Labor productivity increases following a foreign acquisition, though the results are not significant until the second year after the foreign acquisition. Similarly, exporting does not improve labor productivity. The results show that exporting might have a negative impact on labor productivity, though the results are not statistically significant. Importing increases labor productivity starting from the year when plants start to import and remains so until two years forward. These are consistent with the estimates from DD model when labor productivity is used.

In terms of exporting and productivity, this research lends support the select-selection hypothesis that plants with higher productivity self-select into export market (Bernard and Jensen 1999, Clerides et al 1998, Aw et al 2000), though Blalock and Gertler (2004) find support to the learning effects of exporting using a similar dataset on Indonesia. A number of reasons could have accounted for the differences in conclusions. First, Blalock and Gertler (2004) excluded foreign-owned plants from their sample, but did not take importing into account. Second, their analysis does not distinguish the trajectory of productivity effects following exporting. Third, they use unmatched samples for the time period of 1990-1996 only. As to productivity and foreign ownership/importing, this research finds evidence supporting learning effects. Foreign ownership increases the productivity by a larger margin. The productivity effects from foreign ownership are evident immediately and remain so in the following two years. In contrast, importing has a relatively smaller, though significant, effect on productivity growth. The productivity also jumps immediately, but the effects become much smaller and insignificant afterward.

The difference in productivity effects from different channels of foreign contact might partially come from the sample selection of the foreign partners from more advanced economies. Helpman, Melitz, and Yeaple (2004) developed a model of international trade and investment in which firms can choose to serve their domestic market, to export, or to engage in FDI in order to serve foreign markets. They found that the most productive firms choose to invest in foreign markets while the less productive firms choose to export. In other words, if the foreign partners, acting as the role of professor, are the most productive ones, the outcome of the technology transfer to a developing economy such as Indonesia should be higher, too. Of course, the modes of the partnership matter, too. Foreign ownership suggests more stable and close partnership in comparison to exporting or importing in the form of outsourcing or subcontracting. Another possible explanation is the difference in returns to scale among different channels of foreign contact (Table 1.5). Although exporting plants are bigger in general, they do not display increasing returns to sale. By contrast, the importing plants have modest returns to scale, resulting in a lower production cost when the plant size grows.

1.6 Conclusion

This paper investigates the relationship between international market linkage and productivity at plant levels. It addresses the question of whether foreign contacts could improve productivity, and if so, which channel of foreign contacts has proven the most effective. This research finds evidence that foreign ownership and importing improve productivity relative to plants with no foreign contacts at all, and the improvement starts from the year of foreign contact. However, for exporters, foreign contact does not appear to boost productivity. The use of propensity score matching in combination with model-based regression framework and detailed plant level data in this paper provides a methodology for controlling possible selection issues that could be employed in other studies of foreign contacts where selection is non-random.

These findings provide new insights into the workings and consequences of establishing foreign contacts. It adds to the knowledge of productivity effects of foreign contacts by considering all three channels of foreign contacts together. It also sheds light to policy-making.

In particular, for governments in developing countries especially that are devising policies encouraging domestic firms to go out, these results suggest that not all the channels of foreign contacts should be treated the same way. Foreign direct investment should be given more incentives since it provides the most effective way for technology transfer.

One limitation of my analysis is the data availability. Although the dataset is large including many production variables, foreign partnership, in the form of exporting, importing or foreign ownership, is a rare phenomenon. As a result, the current analysis is confined to one-channel study (i.e. foreign ownership, or exporting, or importing) and at aggregate level. If the analysis could take account of the interaction of different channels or be carried out at industry levels, it might reveal more interesting pattern.

Table 1.1: Summary Statistics and Plant Characteristics by International Linkages

	Mean	Standard Deviation	Minimum	Maximum
Output (Log)	12.02	1.68	4.06	21.88
Capital (Log)	11.20	1.82	-1.70	22.61
Employment (Log)	3.83	0.94	0.00	11.66
Investment (Log)	10.27	2.23	-1.79	21.68
Material (Log)	10.78	1.98	-1.96	21.53

International Linkages	Employment	Capital (per worker)	Ratio of White-collar Workers	Log of Raw Materials (per worker)
Exporting Plants	4.58	3.49	1.23	1.12
Importing Plants	3.12	5.81	1.47	1.13
Foreign-owned Plants	3.71	3.29	1.52	1.15
Plants Without Any Foreign Contact	1	1	1	1

Note: The five variables in the first panel of the table are the variables used for estimating Olley-Pakes productivity and they are deflated by WPI except for employment. The second panel of the table gives descriptive statistics for most of the variables used in matching. Among them, capital per worker and raw materials per worker are deflated by WPI. The plant characteristics for plants without any foreign contact are normalized to 1.

Table 1.2: Industry Distribution of Plants by Foreign Contacts and Plant Characteristics by Industry

	Frequency				Mean			
	Always None	None → Exp	None → Imp	None → Foreign	Employment	Log of Capital (per worker)	Ratio of White-collar Workers	Log of Raw Materials (per worker)
Food products (311)	2,262	425	192	18	85	7.45	0.16	7.45
Food products, nes (312)	1,885	195	146	11	52	7.25	0.15	6.65
Beverages (313)	232	16	36	8	58	7.72	0.22	5.78
Tobacco (314)	953	55	25	3	187	5.96	0.04	5.70
Textiles (321)	1,825	266	254	16	119	7.28	0.09	6.82
Clothing (322)	1,869	332	101	9	59	7.03	0.07	7.08
Leather goods, nes (323)	155	49	22	0	47	7.37	0.10	7.07
Leather footwear (324)	301	40	20	4	86	7.37	0.11	7.20
Wood and cork, except furniture (331)	1,333	627	34	2	83	7.53	0.15	7.16
Furniture (332)	798	531	47	8	60	7.21	0.11	7.12
Paper and paper products (341)	262	27	36	4	104	7.97	0.17	8.05
Printing, publishing, and allied industries (342)	572	17	81	2	66	8.14	0.21	7.45
Industrial chemicals (351)	231	50	42	10	98	8.23	0.23	7.48
Other chemical products (352)	227	35	89	6	78	7.74	0.24	7.58
Rubber products (355)	212	136	38	2	142	7.93	0.22	6.44
Plastic products, nes (356)	651	46	119	6	74	7.72	0.13	6.73
Pottery, china and earthwear (361)	31	8	9	1	97	7.56	0.12	5.72
Glass and glass products (362)	46	8	8	1	113	7.15	0.14	6.70
Cement (363)	629	25	37	9	51	7.48	0.15	7.01
Clay products (364)	1,121	18	13	3	37	6.72	0.05	5.08
Other nonmetallic mineral products (369)	304	39	20	3	49	7.69	0.17	6.62
Iron and steel industries (371)	53	5	28	0	121	8.42	0.20	8.38
Nonferrous metal basic industries (372)	33	8	9	1	77	7.87	0.21	8.02
Fabricated metal products, except machinery (381)	856	58	103	12	68	7.55	0.13	7.47
Nonelectrical machinery (382)	246	22	36	2	61	8.15	0.14	6.96
Electrical machinery (383)	195	14	53	6	88	7.87	0.19	7.60
Transport equipment (384)	497	34	52	5	85	7.76	0.17	7.16
Professional, scientific, and equipment (385)	39	4	8	3	45	7.46	0.10	6.97
Miscellaneous manufacturing (390)	374	90	28	4	58	6.90	0.10	6.93

Note: Always none refers to the plants that do not have any foreign contacts during the sample period. None → exp refers to the plants that are not exporting initially and enter the export market in the sample period. None → imp and none → foreign are similarly defined for the import market and foreign acquisition.

Table 1.3: Estimates of Production Functions

Industry	Labor		Materials		Capital	
	OLS	OP	OLS	OP	OLS	OP
Food products (311)	0.357	0.338	0.677	0.676	0.097	0.049
Food products, nes (312)	0.370	0.330	0.473	0.440	0.240	0.101
Beverages (313)	0.886	0.670	0.316	0.241	0.267	0.203
Tobacco (314)	0.288	0.235	0.791	0.764	0.077	0.001
Textiles (321)	0.440	0.358	0.545	0.524	0.160	0.070
Clothing (322)	0.472	0.382	0.538	0.552	0.108	0.048
Leather goods, nes (323)	0.406	0.322	0.624	0.599	0.099	0.012
Leather footwear (324)	0.428	0.345	0.560	0.567	0.071	0.024
Wood and cork, except furniture (331)	0.369	0.329	0.623	0.598	0.088	0.046
Furniture (332)	0.391	0.407	0.595	0.551	0.081	0.023
Paper and paper products (341)	0.300	0.266	0.671	0.636	0.107	0.041
Printing, publishing, and allied industries (342)	0.501	0.377	0.555	0.533	0.094	0.030
Industrial chemicals (351)	0.276	0.302	0.535	0.392	0.268	0.081
Other chemical products (352)	0.443	0.476	0.601	0.505	0.135	0.101
Rubber products (355)	0.270	0.235	0.662	0.636	0.073	0.074
Plastic products, nes (356)	0.318	0.242	0.641	0.641	0.116	0.039
Pottery, china and earthwear (361)	0.329	0.291	0.610	0.523	0.143	0.087
Glass and glass products (362)	0.523	0.375	0.616	0.557	0.082	0.119
Cement (363)	0.433	0.302	0.666	0.626	0.103	0.069
Clay products (364)	0.549	0.510	0.409	0.391	0.178	0.105
Other nonmetallic mineral products (369)	0.462	0.348	0.556	0.540	0.181	0.154
Iron and steel industries (371)	0.345	0.308	0.674	0.683	0.100	0.108
Nonferrous metal basic industries (372)	0.388	0.295	0.607	0.520	0.155	0.143
Fabricated metal products, except machinery (381)	0.348	0.271	0.638	0.617	0.109	0.031
Nonelectrical machinery (382)	0.405	0.327	0.561	0.533	0.180	0.139
Electrical machinery (383)	0.318	0.286	0.666	0.629	0.105	0.095
Transport equipment (384)	0.445	0.393	0.573	0.521	0.145	0.062
Professional, scientific, and equipment (385)	0.542	0.359	0.573	0.524	0.072	0.043
Miscellaneous manufacturing (390)	0.487	0.448	0.514	0.451	0.117	0.081

Table 1.4: Average Productivity of Indonesian Plants by International Linkages, 1993-2001

International Linkages	Olley-Pakes	Log of Value-added Per Worker
Exporting Plants	1.05	1.07
Importing Plants	1.07	1.09
Foreign-owned Plants	1.13	1.12
Plants Without Any Foreign Contact	1	1

Note: The estimated productivity for plants without any foreign contact is normalized to 1.

Table 1.5: Coefficient Estimates for the Production Function by International Linkages

International Linkages	Labor	Materials	Capital	RTS
Exporting Plants	0.259	0.605	0.073	0.937
Importing Plants	0.380	0.550	0.115	1.045
Foreign-owned Plants	0.323	0.564	0.088	0.975
Plants Without Any Foreign Contact	0.369	0.531	0.087	0.987

Note: RTS is the return to scale. The coefficient estimates are obtained by performing Olley-Pakes procedure to estimate the production function.

Table 1.6: Pair-wise Logit Model: Propensity Scores

Dependent Variable	Foreign Ownership	Exporting	Importing
Age	-0.197***	-0.048***	0.005
	[0.053]	[0.010]	[0.014]
Employment	1.092*	1.715***	1.116***
	[0.617]	[0.121]	[0.171]
Employment Squared	-0.053	-0.089***	-0.054***
	[0.062]	[0.012]	[0.017]
Ratio of White-collar Workers	0.922*	-0.035	0.237
	[0.561]	[0.132]	[0.181]
Capital Intensity	0.296***	0.006	0.172***
	[0.073]	[0.015]	[0.022]
Raw Materials	0.153**	0.201***	0.111***
	[0.065]	[0.014]	[0.019]
Productivity at t'	0.231**	0.151***	0.158***
	[0.100]	[0.022]	[0.031]
# of Observations	59,641	62,339	60,834
Chi-squared	121	3,029	824
Pseudo R-squared	0.0819	0.1326	0.0659

Regression is carried using the information at one period before the foreign contact. Except for age and ratio of white-collar workers, all the other independent variables are in logs. Productivity at t' controls the total factor productivity (Olley-Pakes) at one period before the foreign contact. *=0.10, **=.05, ***=.01

Table 1.7: Balancing Test between Plants Without Foreign Contact and Foreign-owned Plants

		Means				t-test
Variables	Sample	Treated	Control	SDiff	%reduct in Sdiff	t-stat
Age	Unmatched	2.11	3.30	-56.39		-4.91
	Matched	2.11	2.00	6.20	89.0	0.77
Capital Intensity	Unmatched	8.28	7.28	65.41		7.15
	Matched	8.28	8.24	2.50	96.2	0.26
Employment	Unmatched	4.40	3.67	74.71		9.52
	Matched	4.40	4.32	7.56	89.9	0.92
Employment Squared	Unmatched	20.71	14.06	71.79		9.79
	Matched	20.71	19.88	7.66	89.3	0.86
Ratio of White-collar Workers	Unmatched	0.20	0.12	46.51		5.30
	Matched	0.20	0.20	0.89	98.1	0.08
Raw Materials	Unmatched	8.90	8.27	40.01		3.96
	Matched	8.90	8.81	6.10	84.8	0.56
Productivity at t'	Unmatched	4.24	3.92	33.09		3.65
	Matched	4.24	4.27	-1.94	105.9	-0.34

Note: SDiff is calculated based on the formula in section 1.3.2. The t-statistics are obtained by regressing each covariate on the foreign contact indicator. Productivity at t' controls the total factor productivity (Olley-Pakes) at one period before the foreign contact.

Table 1.8: Balancing Test between Plants Without Foreign Contact and Exporting Plants

		Means				t-test
Variables	Sample	Treated	Control	SDiff	%reduct in Sdiff	t-stat
Age	Unmatched	2.82	3.30	-21.36		-10.21
	Matched	2.82	2.62	10.56	50.6	6.60
Capital Intensity	Unmatched	7.62	7.28	23.01		12.54
	Matched	7.62	7.48	9.00	60.9	3.61
Employment	Unmatched	4.69	3.67	98.74		66.74
	Matched	4.69	4.65	3.07	96.9	3.60
Employment Squared	Unmatched	23.54	14.06	92.94		69.24
	Matched	23.49	23.07	3.44	96.3	3.64
Ratio of White-collar Workers	Unmatched	0.15	0.12	21.02		11.60
	Matched	0.15	0.15	1.39	93.4	0.56
Raw Materials	Unmatched	8.94	8.27	40.77		21.75
	Matched	8.94	8.93	0.24	99.4	0.11
Productivity at t'	Unmatched	4.12	3.92	23.31		11.96
	Matched	4.12	4.11	0.90	96.1	0.58

Note: SDiff is calculated based on the formula in section 1.3.2. The t-statistics are obtained by regressing each covariate on the foreign contact indicator. Productivity at t' controls the total factor productivity (Olley-Pakes) at one period before the foreign contact.

Table 1.9: Balancing Test between Plants Without Foreign Contact and Importing Plants

Variables	Sample	Treated (Means)	Control (Means)	SDiff	%reduct in Sdiff	t-test t-stat
Age	Unmatched	2.96	3.30	-14.82		-5.03
	Matched	2.96	2.93	1.44	90.3	0.77
Capital Intensity	Unmatched	7.86	7.28	38.94		14.87
	Matched	7.86	7.88	-1.06	102.7	-0.34
Employment	Unmatched	4.34	3.67	68.45		30.62
	Matched	4.34	4.31	2.90	95.8	1.75
Employment Squared	Unmatched	20.14	14.06	64.12		31.40
	Matched	20.14	19.83	2.75	95.7	1.54
Ratio of White-collar Workers	Unmatched	0.16	0.12	26.36		9.86
	Matched	0.16	0.16	0.29	98.9	0.09
Raw Materials	Unmatched	8.78	8.27	33.28		11.37
	Matched	8.78	8.81	-2.34	107.0	-0.75
Productivity at t'	Unmatched	4.14	3.92	24.36		8.89
	Matched	4.14	4.11	3.15	87.1	1.49

Note: SDiff is calculated based on the formula in section 1.3.2. The t-statistics are obtained by regressing each covariate on the foreign contact indicator. Productivity at t' controls the total factor productivity (Olley-Pakes) at one period before the foreign contact.

Table 1.10: Estimated Effects of Foreign Contact on Productivity (ATT), Propensity Score Matching

	Foreign Ownership		Exporting		Importing	
	DD	Std. Error	DD	Std. Error	DD	Std. Error
Olley-Pakes						
Year of Foreign Contact	0.357**	0.178	-0.022	0.020	0.068**	0.033
One Year After Foreign Contact	0.225	0.204	-0.035	0.023	0.004	0.042
Two Year After Foreign Contact	0.319	0.200	-0.048	0.031	-0.018	0.048
Labor Productivity						
Year of Foreign Contact	0.492	0.374	-0.045	0.047	0.248***	0.065
One Year After Foreign Contact	0.643**	0.314	-0.057	0.054	0.136**	0.072
Two Year After Foreign Contact	0.947***	0.284	0.082	0.060	0.188***	0.078

Table 1.11: Compare the Productivity Effects of Different International Linkages Using Matched and Unmatched Samples

	Matched Samples[1,2]			Unmatched Samples[1,2]		
	Foreign Ownership	Exporting	Importing	Foreign Ownership	Exporting	Importing
International Linkages[3]	0.204*	0.025	0.083***	0.219***	0.050***	0.065***
	[0.108]	[0.018]	[0.024]	[0.047]	[0.012]	[0.021]
Age	0.023	0.037***	0.015**	0.031***	0.028***	0.030***
	[0.019]	[0.006]	[0.007]	[0.001]	[0.001]	[0.001]
Employment	-0.599	0.073	0.139	0.136***	0.112***	0.143***
	[0.404]	[0.100]	[0.124]	[0.030]	[0.037]	[0.035]
Employment Squared	0.058	-0.018*	-0.017	-0.020***	-0.016***	-0.021***
	[0.041]	[0.010]	[0.012]	[0.003]	[0.004]	[0.004]
Ratio of White-collar Workers	-0.186	0.464***	0.371***	0.049**	0.055**	0.063**
	[0.263]	[0.091]	[0.095]	[0.023]	[0.027]	[0.026]
Capital Intensity	-0.002	0.015	-0.031**	-0.021***	-0.024***	-0.021***
	[0.043]	[0.009]	[0.016]	[0.003]	[0.003]	[0.003]
Raw Materials	0.014	0.029*	0.035*	0.004	0.007	0.004
	[0.046]	[0.017]	[0.018]	[0.006]	[0.007]	[0.007]
# of Observations	214	8,284	3,981	124,565	106,332	101,376
R-squared	0.88	0.71	0.81	0.88	0.89	0.89

1. The international linkage dummy variables in the unmatched samples are generated without consideration of other channels of foreign contacts. For example, foreign ownership dummy variable indicates foreign-owned plants regardless of the plant's exporting or importing status. By contrast, the international linkage variable dummy variables in the matched samples refer to plants with only one channel of foreign contact.
2. The regressions on matched samples are carried out with pairwise fixed effects model and the standard errors are clustered at plant levels, while the regressions on the unmatched samples are carried out with plant fixed effects models and the standard errors are clustered at plant levels.
3. The international linkage dummy variables are created to indicate the period after foreign contact. Normally it includes the year of establishing foreign contact, one year after and two years after the foreign contact.

Table 1.12: Productivity Effects of Different International Linkages, Matched Samples[1]

	Foreign Ownership			Exporting			Importing		
	Year of Foreign Contact	One Year Forward	Two Years Forward	Year of Foreign Contact	One Year Forward	Two Years Forward	Year of Foreign Contact	One Year Forward	Two Years Forward
Foreign Contact	0.333*	0.23	0.417**	0.0005	0.016	0.063***	0.083***	0.048	0.054
	[0.198]	[0.199]	[0.179]	[0.019]	[0.020]	[0.023]	[0.031]	[0.034]	[0.034]
Age	0.129	0.405***	0.272***	-0.036***	-0.016	-0.044***	-0.054	-0.079**	-0.060*
	[0.165]	[0.126]	[0.101]	[0.011]	[0.011]	[0.013]	[0.033]	[0.036]	[0.036]
Employment	-0.836	-1.599	-2.449**	0.739**	0.584*	1.030***	-0.052	0.038	-0.166
	[1.524]	[1.144]	[0.917]	[0.293]	[0.312]	[0.335]	[0.419]	[0.466]	[0.454]
Employment Squared	0.072	0.084	0.177**	-0.048**	-0.040*	-0.062**	0.003	-0.008	0.01
	[0.128]	[0.097]	[0.075]	[0.020]	[0.022]	[0.024]	[0.032]	[0.035]	[0.031]
Ratio of White-collar Workers	-0.047	-1.664***	-1.214**	-0.138	-0.136	-0.084	-0.215	-0.042	0.025
	[0.785]	[0.514]	[0.489]	[0.108]	[0.122]	[0.136]	[0.156]	[0.177]	[0.212]
Capital Intensity	-0.127	-0.491***	-0.397***	0.020*	0.014	0.02	-0.008	0.005	-0.043
	[0.227]	[0.164]	[0.124]	[0.011]	[0.012]	[0.013]	[0.046]	[0.052]	[0.055]
Raw Materials	0.026	-0.145	-0.11	0.067**	0.052*	0.082***	0.024	0.016	0.009
	[0.100]	[0.097]	[0.084]	[0.027]	[0.028]	[0.027]	[0.034]	[0.038]	[0.041]
Productivity at t'[2]	0.062	-0.335	-0.268	0.883***	0.866***	0.801***	0.597***	0.494***	0.408***
	[0.231]	[0.222]	[0.197]	[0.038]	[0.037]	[0.043]	[0.065]	[0.072]	[0.089]
# of Observations	46	46	46	1,452	1,452	1,452	758	758	758
R-squared	0.93	0.94	0.95	0.91	0.91	0.88	0.92	0.89	0.90

1. The regressions are carried out with pairwise fixed effects model and the standard errors are clustered at plant levels.
2. Productivity at t' controls the total factor productivity (Olley-Pakes) at one period before the foreign contact.

Table 1.13: Labor Productivity Effects of Different International Linkages, Matched Samples[1]

	Foreign Ownership			Exporting			Importing		
	Year of Foreign Contact	One Year Forward	Two Years Forward	Year of Foreign Contact	One Year Forward	Two Years Forward	Year of Foreign Contact	One Year Forward	Two Years Forward
Foreign Contact	0.028	0.262	0.749**	-0.039	-0.053	-0.02	0.244***	0.194***	0.241***
	[0.376]	[0.326]	[0.293]	[0.038]	[0.042]	[0.045]	[0.058]	[0.064]	[0.065]
Age	-0.597	-0.028	0.303	-0.063***	-0.055**	-0.034	-0.054	-0.091	-0.158**
	[0.465]	[0.406]	[0.222]	[0.021]	[0.023]	[0.029]	[0.083]	[0.079]	[0.069]
Employment	5.364	-1.163	-2.613	1.215*	1.380*	0.229	-0.287	-0.899	-0.776
	[5.810]	[4.600]	[3.291]	[0.651]	[0.710]	[0.990]	[1.307]	[0.770]	[0.732]
Employment Squared	-0.382	0.114	0.16	-0.086*	-0.085*	-0.003	0.044	0.049	0.047
	[0.471]	[0.369]	[0.276]	[0.046]	[0.050]	[0.065]	[0.086]	[0.057]	[0.057]
Ratio of White-collar Workers	0.593	0.708	-1.403	-0.139	-0.097	0.037	-0.151	-0.183	0.229
	[2.249]	[2.213]	[1.522]	[0.222]	[0.256]	[0.297]	[0.299]	[0.330]	[0.300]
Capital Intensity	0.821	-0.19	-0.534	0.072***	0.034	0.058**	0.103	-0.037	-0.073
	[0.858]	[0.747]	[0.501]	[0.022]	[0.024]	[0.028]	[0.139]	[0.075]	[0.070]
Raw Materials	0.497*	0.301	-0.109	0.104**	0.112**	0.056	0.103*	0.106**	0.096**
	[0.268]	[0.227]	[0.204]	[0.045]	[0.048]	[0.070]	[0.059]	[0.043]	[0.040]
Labor Productivity at t'[2]	1.221*	0.763	0.112	0.680***	0.698***	0.557***	0.622***	0.265**	0.235**
	[0.613]	[0.460]	[0.287]	[0.060]	[0.061]	[0.097]	[0.211]	[0.120]	[0.112]
# of Observations	46	46	46	1,450	1,450	1,450	758	758	758
R-squared	0.78	0.80	0.81	0.76	0.72	0.68	0.79	0.74	0.73

1. The regressions are carried out with pairwise fixed effects model and the standard errors are clustered at plant levels.
2. Labor productivity at t' controls labor productivity at one period before the foreign contact.

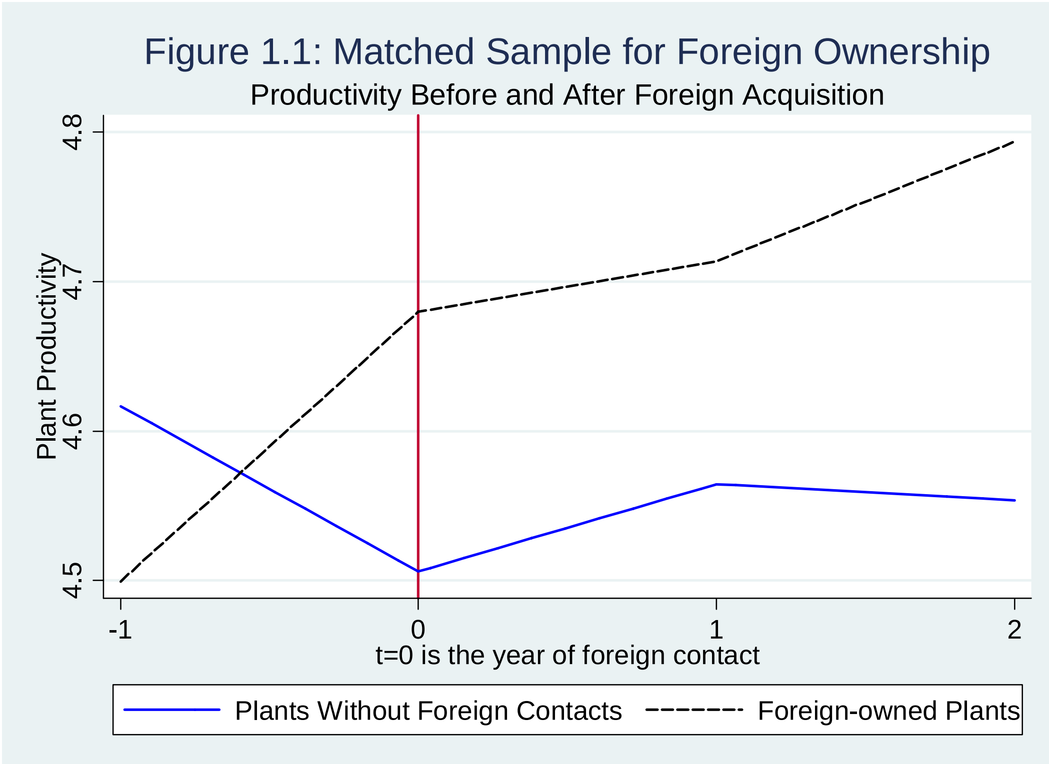
Figure 1.1: Matched Sample for Foreign Ownership
Productivity Before and After Foreign Acquisition
Plant Productivity
4.5
4.6
4.7
4.8
-1
0
1
2
t=0 is the year of foreign contact
Plants Without Foreign Contacts
Foreign-owned Plants

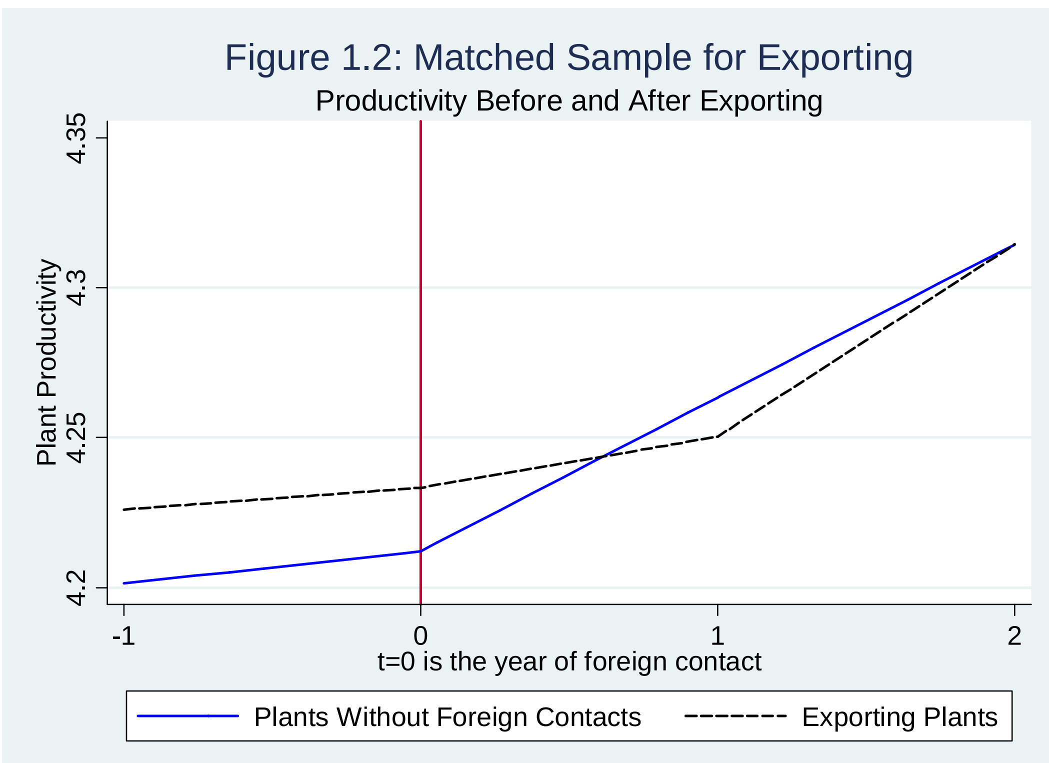
Figure 1.2: Matched Sample for Exporting
Productivity Before and After Exporting
Plant Productivity
4.2
4.25
4.3
4.35
-1
0
1
2
t=0 is the year of foreign contact
Plants Without Foreign Contacts
Exporting Plants

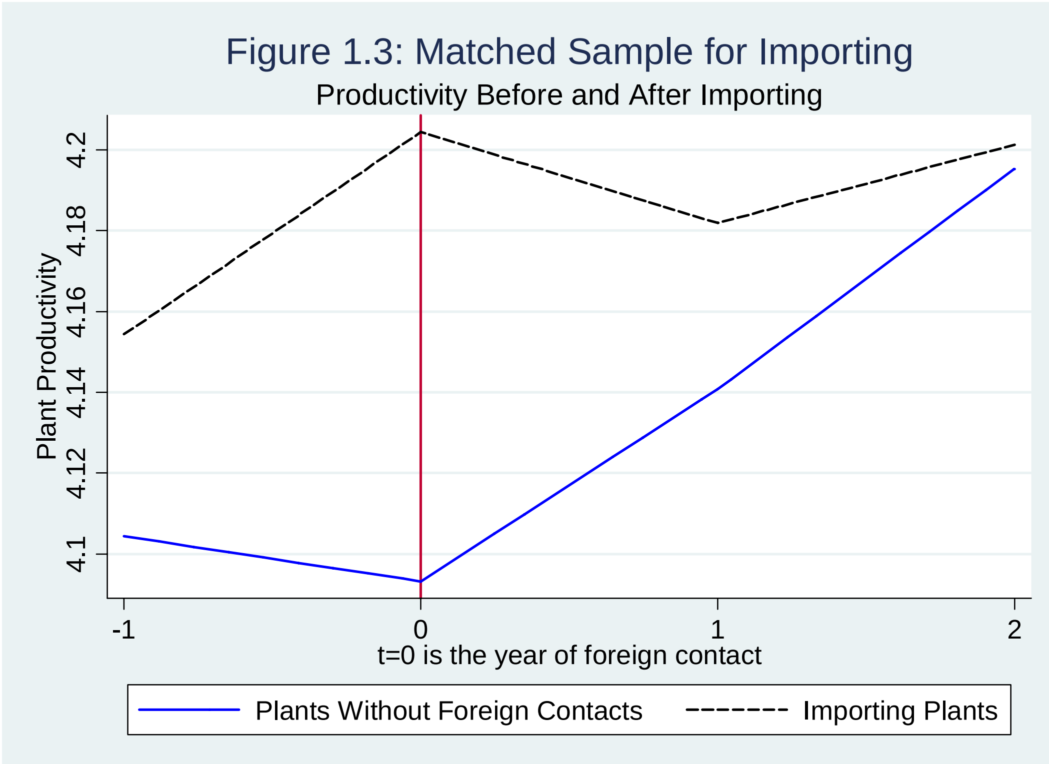
Figure 1.3: Matched Sample for Importing
Productivity Before and After Importing
Plant Productivity
4.1
4.12
4.14
4.16
4.18
4.2
-1
0
1
2
t=0 is the year of foreign contact
Plants Without Foreign Contacts
Importing Plants

Appendix I

1. Data Cleaning Operation

The dataset has been cleaned to minimize nonreporting and obvious typing mistakes during data input. The major adjustments include the following. First, I filled in the gaps if a plant reported for a particular variable no value in a given year using the information before and after that year. This applies to ownership, province and industry classification. Second, plants with unrealistically large spikes in the data are dropped (e.g., employment growth is above the 99 percentile). Third, the capital stock is measured by the replacement value of fixed assets, however, for the year 1996 this information was missing. The capital stock for the year 1996 is then interpolated using the 1997 and 1995 values.

2. Deflators

Output deflators: The wholesale price indices (WPI) are published monthly in the Buletin Statistik Bulanan Indikator Ekonomi of the Indonesian Statistical Agency (Badan Pusat Statistic, BPS), the Monthly Statistical Bulletin of Economic Indicators. I used an unpublished concordance from the BPS to map the 192 WPI commodity codes into the five-digit ISIC industry codes. The WPI at five-digit ISIC is then aggregated into four-digit ISIC using output as the weights since the productivity measure is estimated at four-digit levels.

Material Input deflators: Each four-digit ISIC is mapped to a nearest commodity or industry, and then use the WPI for the corresponding commodity or industry as the material input deflators.

Capital deflator: The capital price deflator was constructed by making use of the aggregate price index of imported electrical and non-electrical machinery and equipment, imported transport goods, and the wholesale price index of manufactured construction materials. I used the information from the SI to compute the shares of vehicles, buildings and equipment at the four-digit ISIC level. Those shares are used to weight each of the individual aggregate deflator to obtain a capital deflator at the sector level.

Part II:

The Impact of China's Export Boom on Exports by Investing Countries

2.1 Introduction

China's exports have grown rapidly in the last few decades. In 1962, China's aggregate export market shares in the world was 0.5 percent, less than half the size of India's, but in 2006, China's export market share had risen to close to 10 percent, higher than Japan's and America's (Figure 2.1)[1]. This raises two questions. What is the main driver for China's export growth? And what are the implications for the other economies? Foreign direct investment (FDI) is shown to have contributed to China's export growth (Blonigen and Ma 2010, Manova and Zhang 2009). However, little has been done on how the investment in China affects the exports by its investing countries. This question has important implications to the economies that invest in China. If the investment in China crowds out the production and exports by the investing country, China's exports would have a negative impact on the economic growth of the investing country, especially if the investing country is an export-oriented economy. Alternatively, if the investment in China boosts the production and exports by the investing country through providing valuable intermediate inputs at lower cost and helping the investing country to move up the value chain, the efficiency of the investing economy will improve, and there could be sizable distribution effects as the investing country concentrates more on the high-end products or high-value products[2].

The investment in China turns on production and cost considerations that might take several forms. The investment could move the production of the products that has become costly to be produced in home countries to China[3]. The production origin of this particular product to a

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[1] Figure2.1 also shows that, when products related to raw materials are excluded , China's export growth displays a similar pattern. The products excluded are SITC 2, SITC 3, SITC 4, and SITC 9.

[2] Krugman (2008) argued that the relationship between imports from developing countries and the wage inequality should be revisited. He explained that, although developing countries are exporting skill-intensive products such as computer, they are specializing in the unskilled-intensive niches within these industries. Consequently, the impact on wage inequality could be significant.

[3] The hypothesis of product cycle is first proposed by Vernon (1966).

third market would be shifted from the investing country to China. This suggests a crowding out effect of China's exports on the exports by its investing countries, assuming the investing countries export the same products. Alternatively, the shift of production to China may raise the return to domestic production in the investing countries, thereby stimulating the economic activity in investing countries including the exports of high-end products of the same category[4] or other high-value products. The resources in home countries could be reallocated from the inefficient production of low-end products to the production of high-value products with efficiency.

To study this question, one problem is the paucity of detailed data on foreign direct investment in China and its investing countries, especially those from developing Asia[5]. This paper sidesteps the data issue by directly linking the exports by China and its investing countries. China's exports provide a good proxy for its investing countries' production in China since the foreign firm's share of China's exports is increasing over time (Blonigen and Ma 2010). To my best knowledge, no study has been done to assess how China's exports have affected its investing countries' exports. This research fills the gap by adding to the knowledge of how the production in the FDI host country could affect home exports.

The paper finds that China's export growth concentrates on the low-tech and high-tech sectors in the period of 1990-2006. Consistent with the related literature, the paper finds that, over time, China's export bundle is increasingly similar to that of its investing countries. The estimation results from a gravity equation suggest that China's exports have a positive impact on

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[4] Vernon (1966) used the textile industry as an example for this. The production of cotton sheetings and men's shirt plants was shifted out of US in search of other low-cost production locations, while producers of high-style dresses or other unstandardized items were far more reluctant to move. However, due to the product aggregation and classification, trade statistics would show this phenomenon as trade of the same products, although there is intra-product differentiation.

[5] Foreign direct investment data, when available, may be distorted in some of China's investing countries for political reasons and for the purpose of avoiding taxes through using tax havens. There is more discussion on this issue later.

the exports by its investing countries, and the results remain robust to various sample sensitivity analysis and to econometric methodologies used. The conclusion is that China's export growth does not crowd out the exports by its investing countries. For the export-oriented investing countries from Asia, their economic growth should not be affected by China's export boom. However, domestically, there would be income distribution effects in the investing countries when they move up the value chain and shift out the production of low-end products to a low-cost country such as China.

This remainder of the paper is organized in the following way. Section 2.2 reviews previous evidence in this issue. In Section 2.3, I study the exports of China and its main investing countries over time, across sectors and across export markets. Section 2.4 discusses the relationship between China's exports and its investing countries' exports by constructing an export similarity index (ESI). The focus is to see how China's exports resemble those of its investing countries over time. Section 2.5 examines the relationship between Chinese exports and the investing countries' exports using the gravity equation. Section 2.6 concludes.

2.2 Literature Review

Multinational companies are conduits of capital, technology, and knowledge of world markets. Their decisions on the location of production could change the trade pattern in both home and host countries. Blomström, Lipsey, and Kulchcky (1988) used US and Swedish data and reported that the relationship between foreign production and home countries' exports is something between neutrality and complementarity. Kim (2000) studied the same question in the context of Korea in early 1990s and concluded a positive relationship between the foreign production and home exports, especially the foreign production in developing countries. Some literature focuses on FDI and host countries' exports. For example, Lipsey (2000) demonstrates how FDI from US and Japan transformed the comparative advantages of eight Asian economies studied.

Much of the recent theoretical and empirical work on foreign direct investment emphasizes another motivation for the investment. Specifically, Hummels, Shii and Yi (2001), Yi (2003) and Yi (2010) emphasize the importance of vertical specialization to international trade pattern. Such vertical specialization, or production sharing, means that the origin of any particular manufactured product cannot be attributed to a single country. The trade statistics could thus give a biased picture, leading to the debate about the sophistication of China's exports. Rodrik (2006) constructed a measure of productivity level associated with a country's export basket and argued that a distinct feature about China's exports is that its export bundle is that of a country with an income per capita level three times higher than China's. However, this may not reflect how much value is added by Chinese production. By decomposing China's export growth in recent years, Amiti and Freund (2007) found that processing trade is the major driver for China's stellar trade performance and the skill content of Chinese exports has changed little. Similarly, using disaggregated product-level US import data, Schott (2008) showed that the overlap of China's export bundle with that of OECD has increased rapidly in the US market. Cui and Syed (2007), using disaggregated trade data, demonstrated that China has moved away from traditional assembly operations and its exports have started to rely more on domestically sourced components, particularly in less sophisticated product categories.

Much of the literature on the impact of China's growing exports relates China's exports to the exports by developing countries with similar low labor cost. Eichengreen, et al (2007) used IMF DOT data to study the impact of China's exports on other Asian countries and found that crowding-out effects by China's export are mainly felt in consumer goods and by less developed Asian countries. They also found that China's rising demand for imports of capital goods helps to increase exports by more advanced Asian economies. A similar study by Hanson and Robertson (2010) on several developing countries that have a high proportion of manufacturing exports showed that China's export expansion has only a modest negative shock to these countries.

2.3 Export Evolution of China and Its Investing Countries

I first answer the question of identifying the source of China's export growth by tracking the exports of China's and its investing countries over 1962-2006. The data used in this paper is a combination of the NBER trade statistics (Feenstra, et al, 2005) for the period of 1962-2000 and UN Comtrade database for the period of 2001-2006[6]. The data are classified by SITC Rev. 2 at four-digit levels. The basic analysis is conducted by excluding exports of fuel, raw materials, and "other goods not elsewhere specified", mostly to avoid the distortions resulting from highly volatile oil and commodity prices. In the analysis of export performance and in the regression analysis, the products are aggregated into 12 broad product groups, which are then allocated according to their technological intensity into 3 broad categories (low-, medium- and high-tech)[7]. The classification of products follows ECB (2005). In terms of geographical breakdown, exports cover the 11 destination markets including China, Japan and nine regions[8].

China's aggregate FDI data are used to identify its main investing countries. China's FDI inflows are mainly from Asian economies, which accounted for three quarters of China's total

[6] The NBER trade statistics was also obtained from UN Comtrade database and it cleaned up the inconsistency reporting of trade statistics in UN Comtrade database (Feenstra, et al 2005). Therefore, there is no continuity issue. The export performance analysis in the following section shows the continuity of the data.

[7] Details of the classification of sectors into high, medium, and low-tech sectors are given in Appendix Table 2.2.

[8] Details on geographical breakdown are in Appendix Table 2.3.

FDI inflow in 1997 and have stayed at a high level since then (Appendix Table 2.1). Data on FDI in China by country are not available in early 1980s except for US, but various evidence suggests that Asia was the major source for China's FDI even then[9]. Among investing countries from Asia, Asian Four Tigers (Hong Kong, Korea, Singapore, and Taiwan) and Japan are the main countries. United States, Germany and United Kingdom are the main investing countries in China from western industrialized countries.

Moreover, Appendix Table 2.1 shows that Virgin Islands is an important investor in China. However, Virgin Islands, Cayman Islands, and Samoa are tax havens without much real production at home. There are a few reasons why there is substantial investment in China from these countries[10]. But this is not the focus of the paper. The omission of these countries should not cause any bias since I relate the exports of China to the exports of its investing countries directly without using data on foreign direct investment. However, similar problem arises with Hong Kong and Singapore where a significant amount of investments are channeled from foreigners through local holding companies to other foreign countries[11]. But Hong Kong and Singapore are different from tax havens such as Virgin Islands, etc. The holding companies in these two economies are largely operated by local residents who are empowered to make investment decisions and the increasing sophistication of local firm management makes the holding firms more in common with locally controlled firms (Low et al 1998). Therefore, their

[9] Using data in late 1980s and early 1990s, Wei (2000) documented that, despite the fact that China has become "the world's strongest magnet for overseas investment", its inward foreign direct investment mainly comes from Asian economies such as Hong Kong, Taiwan, Macao, and Singapore. China is still an underachiever as a host of direct investment from the world's major source countries, like the United States, Japan, Germany, and the United Kingdom.

[10] Investment from Taiwan could go through these tax havens given the caps on investment in China by Taiwan administration. In addition, some investment from China itself might go through tax havens and then come back to China to take advantage of the tax preferences given to foreign investors. This is so-called round-tripping investment. Huang (1998) estimated the round-tripping FDI through Hong Kong. However, as I use FDI data only to identify the main investing countries in China, the round-tripping FDI and the investment from tax havens should not affect the results.

[11] Low, Ramstetter, and Yeung (1998) gives a detailed discussion on this issue.

investment could potentially affect the exports of these two economies and those of the recipient countries such as China. In this paper, China's exports are related to the exports from the following eight economies: Hong Kong, Japan, Korea, Singapore, Taiwan, United States, Germany and United Kingdom.

The export performance and specialization pattern could be analyzed using various measures. In this paper, I first study how export market shares have changed and identify the products/markets that have contributed most to the changes. Furthermore, I compare the changing comparative advantages between China and its investing countries using the revealed comparative advantage (RCA) index, proposed by Balassa (1965 & 1979). The RCA index is a widely accepted approach in analyzing a country's export pattern with consideration of a country's relative size.

2.3.1 Export Market Shares

Export market share measures the extent of a country's foray into world markets. Supposedly, if a country is more competitive in producing some products or in serving some markets, it would have higher market shares in those products or markets. Therefore, changes in market shares over time reveal the sectors or markets that have grown rapidly.

Table 2.1 summarizes China's export market shares by technology intensity over time. During the period studied, China has expanded market shares in all sectors and the expansion in low-tech and high-tech sectors is the most conspicuous. China's expansion in low-tech sectors rose from 1.2 percent in 1960s to almost 13 percent in 2000s and the export market shares in high-tech sectors grew from a tiny 0.08 percent in 1960s to 14.6 percent in recent years. China's expansion in low-tech sectors is consistent with predictions of classical Heckscher-Ohlin model that a country endowed with unskilled labor such as China should export low-tech products. If the foreign investment is motivated by the product cycle as investing countries' domestic wage costs rise and other countries learn how to produce similar products, the investment would help China to develop or strengthen its competitiveness in some particular industries. However, the high-tech sectors are not typically associated with China's comparative advantage. One explanation for China's export boom in high-tech sectors is the growth of international production chains. Investing countries could concentrate the resources on the production of high value-added parts while China specializes in the unskilled-labor-intensive assembling process. Consequently, China's exports are inflated by the high-value parts that are imported from elsewhere and cannot reflect its genuine comparative advantages based on value added. To check China's contribution in the value added chain, Table 2.2 presents China's import market shares by technology intensity. There are upward trends in China's imports in all three technology groups. If the net export shares are considered, China's net export shares in high-tech sectors during the period of 2001-2006 is 5.23 percent, as compared with the 9.49 percent for the low-tech sectors during the same time period. The expanding market shares of China's exports and imports in high-tech sectors both concentrate on the period since 1990s, especially after 2000. This suggests that China's comparative advantages in high-tech sectors should be partly built on the low-tech niche of high-tech production such as assembly.

If China's exports have any impact on its investing countries' exports, the impact should be stronger in the sectors that China's exports have grown the most. For the convenience of comparison, Figure 2.2 compares the evolution of China's export market shares and its investing countries' export market shares in both low-tech and high-tech sectors. In low-tech sectors, the market shares of developed countries including Japan, UK, and US are declining over time, while those of Asian Tigers such as Hong Kong, Korea and Taiwan have an inverted U shape, reaching their peaks in late 1980s. The falling market shares from Asian Tigers since late 1980s was accompanied by the increasing market shares from China since late 1990s. If Asian Tigers started to shift the production of the products that has become too costly to produce at home to China since 1980s, this could result in a rise in China's export market shares in these low-tech products and a corresponding fall in the investing countries. In the high-tech sectors, the market shares of developed countries are declining over time except for Japan, whose market shares reached its peak in 1980s before a gradual drop in 1990s and a sharp fall after 2000. The change pattern in Japan's market shares in high-tech sectors coincides with China's expansion in these sectors. If Japan moves part of the production process to China, China's export values of high-tech sectors include the value added in Japan. Moreover, China's other investing countries from Asia all experienced an increase in the export market shares in high-tech sectors starting from as early as 1970s, but recently their market shares in these sectors remain small in comparison to China's, a reflection of the country size. When the RCA index is used to evaluate the export pattern, the influence of a country's size on export specialization would be removed. The different trends in export market shares between low-tech and high-tech sectors and among different investing countries point to possibly different relationships of trade and investment.

In terms of destination markets, Table 2.3 tabulates China's export market shares in all the geographical regions. Among them, China's expansion in East Asia, Other Asia, North America, and Japan is the most obvious. When the export market shares are broken down by technology intensity, these four regions remains the main destination markets for China's exports in low-tech and high-tech sectors. China's expansion in low-tech sectors in these regions is in sync with the classical trade theories of comparative advantages and abundant resources. However, the traditional trade theories cannot explain how China could manage to expand the exports from high-tech sectors in Japan and US markets so rapidly in recent years. Yi (2003, 2010) documented that the reduction in trade costs could have magnified effects on the multistage production since the production of one product might cross borders multiple times. This finding suggests that China's trade liberalization since 1990s encourage the processing trade and cause the statistical mirage that China has an export comparative advantage in high-tech products in high-income countries such as Japan and US.

To further explore the relationship of export market shares in high-tech sectors between China and its investing countries, Figure 2.3 shows the evolution of market shares of China and its investing countries in two major markets: North America and Western Europe. Again there are two camps in terms of the general trend in market shares in high-tech sectors. Developed countries such as US, UK, and Germany have declining market shares, while the market shares of the developing economies are climbing. The only exception is Japan, whose market shares are inverted U-shaped with peaks coinciding with China's takeoff. Either Japan is losing its competitiveness in high-tech sectors in recent years, or Japan ships its high-tech parts to China for assembling.

In sum, the export share data suggest that China's competitiveness in low-tech and high-tech sectors has been improving. However, to a growing economy of China's size, export competitiveness, reflected in export market shares, may not reveal the comparative advantages of China. A large economy would probably have bigger shares in world trade because of its size. In the next section, I explore the issue further by studying the changing comparative advantages of China and its investing countries.

2.3.2 Revealed Comparative Advantage (RCA)

Balassa's revealed comparative advantage (RCA) index (Balassa, 1965 & 1979) is an alternative measure of a country's export performance taking into account of an economy's size. In terms of products, RCA is constructed as follows.

$$RCA_i = \frac{X_{i,j} \Big/ \sum_i X_{i,j}}{\sum_j X_{i,j} \Big/ \sum_i \sum_j X_{i,j}} \tag{2.1}$$

where $X_{i,j}$ is export of good i by country j; $\sum_i X_{i,j}$ is total exports by country j; $\sum_j X_{i,j}$ is world exports of good i; $\sum_i \sum_j X_{i,j}$ is total world exports. If $RCA_i > 1$, a country has a comparative advantage in exporting good i. If it is below one, a country has a comparative disadvantage in exporting good i.

Table 2.4 reviews the development of RCA for China in different sectors by technology intensity. In contrast to Table 2.2 where China's market shares are increasing in both low-tech and high-tech sectors since 1962, now China's comparative advantage only gains in high-tech sectors, mostly since 1990s. China has a comparative advantage in low-tech sectors from as early as 1960s and continues to do so, although there are some variations among sectors within the low-tech group. The fact that China's increasing comparative advantages in high-tech sectors is documented in related literature that China's exports are becoming increasingly similar to those of higher income countries (Rodrik 2006). As discussed earlier, this could be a statistical mirage as trade liberalization in China gave rise to processing trade and China simply assembles parts imported from elsewhere. To evaluate China's genuine comparative advantage in high-tech sectors, one needs to trace the sources and destinations of value added along the supply chain of a global industry. This requires a detailed inter-regional input-output (IRIO) table[12]. Even if the distortion in trade statistics are corrected by accurately allocating the value added to the right location, this should not change the fact that China's exports should boost its investing countries' exports if China helps to release the resources in investing countries from inefficient production of low-end products to efficient production of high-value products.

A similar calculation is carried out for China's investing countries. Figure 2.4 presents the results. It shows a remarkable gain in comparative advantages in high-tech sectors for four Asian tigers during late 1970s, while developed economies have either stagnant or declining comparative advantages in these sectors. Japan started to lose its comparative advantages in early 1990s coinciding with China's rise in these sectors. This is consistent with previous findings of Japan's loss in market shares. Japan could lose its comparative advantages as a location for production of high-tech sectors, but its firms could still own the comparative advantages. Kravis and Lipsey (1992) demonstrates the divergence of competitiveness between US and US multinational firms. This evidence leads to the following questions. Is China an export platform for its investing countries, especially those from Asia? Is China's trade relationship with investing countries different across countries? To further explore this issue, next I relate China's exports to the exports by its investing countries by constructing an export similarity index over time.

2.4 Compare China's Exports With Exports of Its Investing Countries

If foreign direct investment restructures China' exports, China's exports should resemble the exports of its investing countries at some point, especially when FDI is mainly coming from

[12] This is an on-going effort to construct a detailed inter-regional input-output tables for specific countries. Literature is emerging in this regard (Koopman et al 2010, Pula and Peltonen 2009, and Wang et al 2009).

the export-oriented developing Asian economies such as Korea, Taiwan and Singapore. To test this hypothesis, I construct an export similarity index (ESI), proposed by Finger and Kreinin (1979) and used in Schott (2008) and Wang and Wei (2010), in the following way:

$$ESI_{k,t} = \sum_i \min\left(s_{ki,t},\ s_{i,t}^{ref}\right) = \sum_j \sum_i \min\left(s_{kij,t},\ s_{ij,t}^{ref}\right) \tag{2.2}$$

where $s_{ki,t}$ is the share of product category i in country k's exports in year t, $s_{i,t}^{ref}$ is the share of product category i in the reference country's (China's) exports in year t. The concept is to construct an index summing the minimum of product category i's shares in either country k or the reference country. The index is bounded by 0 and unity. If country k and China's have no common products exported in year t, then ESI is equal to 0, and if country k and China's have identical products exported in year t, then ESI is equal to 1. The index could also be constructed with more detailed product shares by region or by sector, which may be represented by j in the second equality.

Table 2.5 reports the export similarity between China and its investing countries at a 10-year interval from 1970 to 2006. Over time, there is a trend that China's export bundle is increasingly similar to its investing countries. In 1970, the average ESI is 0.51 and rises to 0.66 in 2006. However, the timing of the increase in ESI is different among China's investing countries. In as early as 1990, China's export bundle started to resemble that of developing Asian economies such as HK, Korea and Taiwan and remains so ever since. For other developed countries, the resemblance is more obvious since 2000. When ESI is constructed with consideration of destination markets, its trend over time stays the same. In this case, the ESI is constructed by comparing China's export market share of product i in destination market j with the corresponding export shares of its investing countries. The average ESI increases from 0.08

in 1970 to 0.25 in 2006. Across investing countries, China's export bundle is more similar to its Asian investing countries.

As the relationship between trade and investment may differ when investors are in different development stages, I estimate the ESI by comparing China's exports to its investing countries exports with 10 years lag. If the ESI with 10 years lag is greater than ESI of the same year, it says that China's exports are more similar to the exports of its investing countries ten years ago. This suggests support for a product cycle hypothesis. If the investing country firms move the production that is no longer consistent with the local comparative advantages to other low cost locations such as China, China's exports would resemble that of its investing countries in the past. Table 2.6 presents the results. For most of the countries in the group, when ESI is calculated with ten years lag, the ESI does not change much except for three economies, Japan, Korea and Taiwan. For these economies, it is clear that, compared to the results from Table 2.5, the exports similarity increases. If similar calculations are done for sectors with different technology intensity, the most obvious discrepancy of the contemporary ESI and ESI with 10 years lag is from low-tech and high-tech sectors for Korea and Taiwan. In both countries, the ESI in low-tech sectors with ten years lag is much higher than the ESI of the same year in both 2000 and 2006, supporting the product cycle hypothesis. In high-tech sectors, the ESI with ten years lag is similar to the ESI of the same year for Korea, but much higher than the ESI of the same year for Taiwan in 2000 as well as 2006. Even if the product cycle hypothesis is supported by this comparison of China's exports and the exports by its investing countries, this is not equivalent to a crowding-out effects from China's exports since the investing countries could concentrate on the high-end products of the same category.

When comparing the exports similarity between China and its investing countries, the results show the variations among countries, sectors and time. In the next section, I apply gravity equation to formally test the relationship between China's exports and its investing countries' exports.

2.5 The Relationship between the Exports by China and the Investing Countries

Although the above evidence suggests that China's exports might follow a different trend from the exports of its investing countries' and that China's exports are increasingly similar to its investing countries despite its relatively low income level, I have not formally identified the influence of China's exports on its investing countries' exports. In this section, I relate China's exports to the exports from its investing countries using gravity equation.

2.5.1 Empirical Estimation Strategy

China's export growth could have different impact on its investing countries' exports depending on the type of production and the motivation of investment. If the investment is motivated by the product cycle and has contributed to China's export boom, China's exports should have a crowding out effect on its investing countries' exports of the same products. By contrast, if China's exports motivate the investing countries to concentrate on the high-end products of the same category or on the high-value production process, the exports by the investing countries could be boosted accordingly.

I rely on the standard gravity model to estimate the trade relationship between China and its investing countries. Gravity model, in the simplest form, suggests that trade is directly proportional to the trading partners' GDP discounted by the distance between them. I augment the basic gravity equation with China's exports and with a number of variables capturing trade costs such as cultural difference and trade barriers[13]. The estimated equation is as follows:

$$In(X_{i,jkt}) =$$
$$\beta_0 + \gamma_1 In(X_{c,jkt}) + \beta_1 In(Y_{jt}) + \beta_2 In(Y_{it}) + \beta_3 In(Y_{jt}/Pop_{jt}) + \beta_4 In(Y_{it}/Pop_{it}) +$$
$$\beta_5 In(D_{ij}) + \beta_6 T_{ijt} + \sum_t \delta_t Year_t + \varepsilon_{i,jkt} \qquad (2.3)$$

where i denotes China's investing countries, j refers to the importing countries, t denotes time, and the variables are defined as:

- $X_{i,jkt}$ denotes the export values of sector k from China's investing country i to an importing country j at time t;
- $X_{c,jkt}$ denotes China's export values of sector k to an importing country j at time t;
- Y is real GDP;
- Pop is population;
- D is the distance between i and j;
- T_{ijt} denotes the variables capturing trade costs between investing countries and the importing countries, both natural and artificial. The variables includes the number of landlocked countries in the country-pair, the number of island nations in the pair, the products of trading partners' land areas, whether sharing a land border, a common language, a common colonizer, being the same nation (e.g. the United Kingdom and Bermuda), ever in a colonial relationship, currently colonized, and belonging to a currency union, and a regional trade agreement, and the Generalized System of Preferences (GSP)[14];

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[13] Trading partners' GDP is incorporated in the model separately to allow for the trade effects of GDP in a flexible way. Also trading partners' GDP per capita is included in the model as these are standard in recent gravity trade literature.

[14] The GSP is a system of exemption from WTO rules extended from rich countries to developing countries. Rose (2004) reported the significant impact of GSP in promoting bilateral trade.

- $Year_t$ is a comprehensive set of time fixed effects;
- $\varepsilon_{i,jkt}$ represents the omitted other influences on bilateral trade.

The coefficient, γ_1, measures the elasticity of exports by the investing countries with respect to China's exports to the same country (of the same sector), and is of main interest in the paper. If China has a lower production cost comparing to its investing countries, this would drive down the world market price for similar products, resulting in a crowding out effect for substitutes. If China's investing countries keep producing the same products, I expect γ_1 to negative. Alternatively, if China's investing countries move the production of low-end products or low-value production process to China and concentrate on high-end products or high-value production process, their exports might be boosted. In this case, I expect γ_1 to positive. The inclusion of China's exports in the estimation equation allows estimating such effects directly. The regression is carried out at both bilateral and sector levels.

All the data used in the paper are publicly available. As described earlier, the nominal trade data comes from the NBER-UN trade data and UN Comtrade database. I used 175 importers including China and the eight selected investing countries. Since such nominal data are recorded in American dollars, I deflate them by the American CPI (1982-1984=100)[15] to obtain the real value, following Rose (2004) and Yu (2010). Real GDP and population data are obtained from Penn World Table 6.3 (Heston et al 2009). Various variables on trade costs are taken directly from Rose (2004) and supplemented by data from CIA and WTO websites. Appendix Table 2.3 gives the descriptive statistics on all the variables used in the regression.

The estimation issue involved is the potential endogeneity problem with China's exports. For example, if France imports more products from both China and Taiwan due to some

[15] Downloaded from US Labor Department in the following website: http://www.bls.gov/cpi/#data.

unobserved factors like the strengthened euro, this results in correlation in the error term and variable of interest. I use both instrumental variable and country-pair fixed effects estimator[16] to solve this issue. For instrumental variable estimation, the instrumental variables[17] include all the gravity variables explaining the bilateral trade between China and a given importer. For instance, the instrumental variables include China's GDP, China's GDP per capita, and the products of areas of China and the trading partners, etc. These gravity variables explain the trade flows between China and its trading partners and thus are correlated with China's bilateral exports, but should not explain the exports by China's investing countries to their trading partners, making them the instruments for China's exports. To precisely estimate the gravity model, Anderson and van Wincoop (2003) emphasized the importance of controlling for "multilateral resistance" among trading partners[18]. To control for multilateral resistance among the trading partners, studies such as Rose and van Wincoop (2001) and Hummels (1999) used country-pair specific fixed effects to control for other unobservable features between each pair of trading countries. I therefore adopt their approach as well in order to check how China's exports could impact the exports from its investing countries.

Alternatively, recent studies carried out by Santos Silva and Tenreyro (2006) and Helpman et al. (2007) have argued that the OLS estimates can cause serious bias due to zero trade volume across trading partners. The log-linearization of directional exports, the dependent

[16] I also performed the importer-year fixed effects and the exporter-year fixed effects. The results are robust and are shown in Appendix Table 2.4.

[17] Another set of instrumental variables that have been experimented is the measure of polity, freedom and civil rights. Yu (2010) explains how democracy and rule of law could promote exports. However, as the polity variables or the freedom scores for China do not vary much over time for the study period, it mostly gives similar results as the instrumental variable estimation from using China's gravity variables as instruments.

[18] Anderson and van Wincoop (2003) refers to the average trade barrier as "multilateral resistance". The intuition, they explained, is that the more resistant to trade with all others a region is, the more it is pushed to trade with a given bilateral partner. In the theoretical model they derived, the multilateral resistance measures the implicit price indexes. To avoid the omitted variable bias, they claimed that the multilateral resistance terms should be added to the estimation equation. They used both nonlinear least squares estimation and fixed effects estimation for the model, and both methods yield similar results.

variable in the estimated equation, may cause some bias since the entire portion of the data with zero trade is dropped. Santos Silva and Tenreyro (2006) proposed a truncated Poisson pseudo-maximum likelihood (PPML) estimation to address the zero trade issue. I therefore estimate the equation (4) with the PPML estimation with the level of the directional exports as the dependent variable following Santos Silva and Tenreyro (2006).

2.5.2 Estimation Results

The benchmark results on bilateral trade relationship are tabulated in Table 2.7a with the first stage estimation shown in Table 2.7b. Table 2.7b shows that the instruments used for China's exports explain a large proportion of the variation in China's exports. Most of the gravity variables are significant and have the expected sign except for regional trade agreement in Table 2.7a. Although the related literature using gravity equation normally has positive coefficient on RTA, the effect of regional trade agreement remains ambiguous (Coulibaly 2009). In Table 2.7a, I presented the estimation results with year effects[19]. The results show that one percent increase in China's exports to an importer is associated with 33 percent increase in investors' exports to that importer, according to OLS estimate. By contrast, when the instrumental variable estimators are used, the impact of China's exports is reduced to approximately 21 percent. If fixed effects estimation is used, the time-constant variables are dropped and the result is similar to the instrumental variable estimation result. The result from

[19] I also carried out the estimation without year fixed effects. The estimated coefficients from OLS estimator and IV estimator are 0.2310 and -0.1475 respectively, both of which are statistically significant at the 1% level. These estimates without year effects are very close to the results reported in Eichengreen et al (2007). However, without effects, the fixed effects and PPML yield similar estimates to those estimated with year effects, suggesting a positive relationship between China's exports and the exports by the investing countries. In this paper, the year effects are added to take account of the common macro shock specific to one year.

PPML gives similar result to the OLS estimate. In general, the results show a fairly large effect of China's exports on the exports from its investing countries.

I present purely cross-sectional evidence in Table 2.8. In particular, I tabulate the estimate of γ_1 when the gravity equation is estimated on individual years at five-year intervals. The gravity regressors are included in the regression, but are not tabulated. Country-pair fixed effects and the year dummies estimates are omitted since there is no variation in a given year. In earlier years, some of the coefficients by IV and PPML are not statistically significant or even negative. However, over time the coefficients are becoming ever larger, indicating that the impact of China's exports is becoming more important in recent years.

Now I run the same regression by time periods. First I run separate regression with year fixed effects for each time period to see how the China effects vary from period to period. Second I run the regression with period fixed effects using the period average to remove the year-to-year fluctuation of export values. Table 2.9 tabulates the key results. The story is similar. China's exports have beneficial effects on its investing countries' exports over time and across different estimation methods. From the regression on different time periods, the estimated effects become bigger over time except for the fixed effects estimates which rather stays stable. The estimates from OLS and PPML are mostly higher than those from instrumental variable and fixed effects estimates. Consistent with the findings from export performance analysis, the effects of China's exports remain positive and become larger since 1990s. The regression with period averages yield similar positive results. These results suggest that, to a particular importer, China's exports have no crowding out effects on its investing countries' exports. This is consistent with the prediction of Schott (2008) which found out that there is intra-product differentiation between China's exports and those from OECD countries in US market.

As China's export boom mostly concentrates on low-tech and high-tech sectors, Table 2.10 tabulates the key results from running the same regression on sectors with different technology intensity. Pooling all years together, the impact of China's exports on its investing countries' exports is positive for all sectors and the effect is more conspicuous on high-tech sectors. Similar regression on two recent decades gives the same conclusion on low-tech and high-tech sectors. However, in medium-tech sectors, the estimates of China's impact are not robust. Since China's export growth concentrates on low-tech and high-tech sectors, its impact on the investing countries' exports should be more conspicuous on these sectors.

In the analysis of market shares in Section 2.3, it is shown that the relationships between China's exports and its investing countries' exports vary across investors. I now allow the effects of China's exports on its investing countries' exports to vary by exporters. Table 2.11 presents the results. When all sectors considered, the first four rows of Table 2.11 show that China's exports have a positive effect on the exports from its western investing countries, Germany, UK and US, and this effect is especially obvious on the exports from Japan, Taiwan and Korea. If similar regression is carried out on low-tech and high-tech sectors, the effects are stronger for Korea and Taiwan in high-tech sectors, but the conclusion remains the same. I did the same regression on a recent period of 1991-2006, the results are robust.

The impact of China's exports on its investing countries could vary by the income levels of destination markets. The first four rows of Table 2.12 tabulate the results by different income groups. The income groups are created using the lists in the World Bank's World Development Indicators (WDI)[20]. The results from OLS, fixed effects and PPML suggest that China's exports have positive effects on its investing countries' exports for all the four income groups. However, the results from instrumental variable estimation reveal a different story. Only in high-income

[20] The WDI database is available online: http://data.worldbank.org/data-catalog/world-development-indicators.

markets, China's exports have a positive effect on its investing countries' exports, while in all the other markets, China's exports have much smaller effects and they are statistically insignificant. This result reveals that China's exports are complementary to its investing countries' exports in differentiated markets. If the product cycle is the driver for the investment in China, then China's exports should be low-end products destined for less differentiated markets. However, if vertical specialization is the reason for investing in China, then China's exports are more likely to be high-tech products since the high-tech products bear the characteristics of high-value relative to the transportation costs and the exports of high-tech products are more likely to target the highly differentiated markets. The last three rows of Table 2.12 present the results for regression on low-tech products destined to low-income or least-income countries and on high-tech products destined to high-income countries. Most of the estimates give a much higher estimate of the China effect for high-tech products destined to high-income countries comparing to the estimates for low-tech products destined to low-income countries.

Overall, the results are robust to various sample sensitivity analysis. Although China's exports may have positive impact the exports by its investing countries in the same year, the crowding-out effect of China's exports may come into play over time as the investment in China could have a lag effect. To account for this possibility, I now run the regression to find out the dynamics of the impact. Table 2.13 shows the results. I run separate regressions and each one includes China's exports one year earlier, or three years earlier, or five years earlier. The contemporary relationship shown in the first row is the same as in Table 2.7 and is listed for comparison. On the whole, OLS estimation gives much bigger impact of China's exports, but the impact is falling over time. In contrast, the estimates from other estimation methods are smaller but stable over time.

Using the gravity equation augmented by China's exports, the regression results show that China's exports actually boost the exports by its investing countries. The results are robust to various sample selections and econometric technologies used. However, as the exports are growing in most countries in recent decades, this raises the question of spurious regression[21]. To rule out the possibility of unit roots, I used the Im-Pesaran-Shin test (Im, Pesaran, and Shin 1997) on the panel data[22] and the hypothesis of unit roots is rejected at the 1% level.

Another way to get at the possible spurious regression is to replace China's exports with the exports by a country that does not receive much investment from China's investing countries and see whether a similar relationship exists. According to UCTADSTAT, Burundi has the lowest total inward FDI stock during the period of 1980 to 2006 in the world. Therefore, I experimented with the exports by Burundi using the same gravity equation above. The results are presented in Table 2.14. The estimates from OLS and fixed effects estimation give a similar positive relationship between Burundi's exports and the exports by China's investing countries, although the magnitude of the estimates is much smaller comparing to the estimates in Table 2.7a. By contrast, the estimates from the instrumental variable estimation and PPML show a negative relationship. Table 2.14 shows that the relationship between Burundi's exports and the exports by China's investing countries is not robust.

2.6 Conclusion

[21] The exports by the investing countries and China's exports could be independent and highly autocorrelated. In fact, if I run the AR(1) autocorrelation on the log of exports by the investing countries or the log of China's exports, the coefficients are approximately 0.95, raising the concern of unit root and thus spurious regression.
[22] The test requires a balanced panel. So I dropped those country pairs with gaps to run the test.

In recent decades, China has grown from having a negligible role in the world trade to becoming the biggest exporter in the world. The exponential growth of China's exports has invited much speculation as to the content of China's export growth and its impact on other countries' exports. This paper studies and compares the exports growth of China's and its investing countries' home countries.

China's expansion in export market shares concentrates on low-tech and high-tech sectors and concentrates in the period since 1990s. There is a general downward trend in export market shares among China's investing countries from developed world, and a similar upward trend in some developing Asian economies. When measured in revealed comparative advantage, China's comparative advantage has grown in high-tech sectors. In particular, China's export growth in high-tech sectors is not consistent with the prediction of trade theory since China is considered abundant with unskilled labor. It is the export growth in high-tech sectors that has invited much speculation on the impact of China's exports on the other economies.

This paper answers the question of the impact of China's exports through estimating an augmented gravity equation and finds that China's exports have a positive impact on the exports from its investing countries. The results are largely not sensitive to the samples or estimation methodologies used. Even when the lagged effects are accounted for, China's exports have persistent positive impact on its investing countries' exports. However, the positive impact of China's exports is stronger for the exports destined for high-income countries.

The investment in China moves the production of low-end products or low-value production process to China and the relatively high-income investing countries could concentrate on high-end products or high-value production process. As a result, their exports are boosted. China's comparative advantage in high-tech sectors is built on the low-tech production process of the high-tech products, a specialization created by the growth of fragmentation of production. The multinationals from investing countries may take advantage of this Chinese comparative advantage and contribute to the competitiveness of the producers in investing countries.

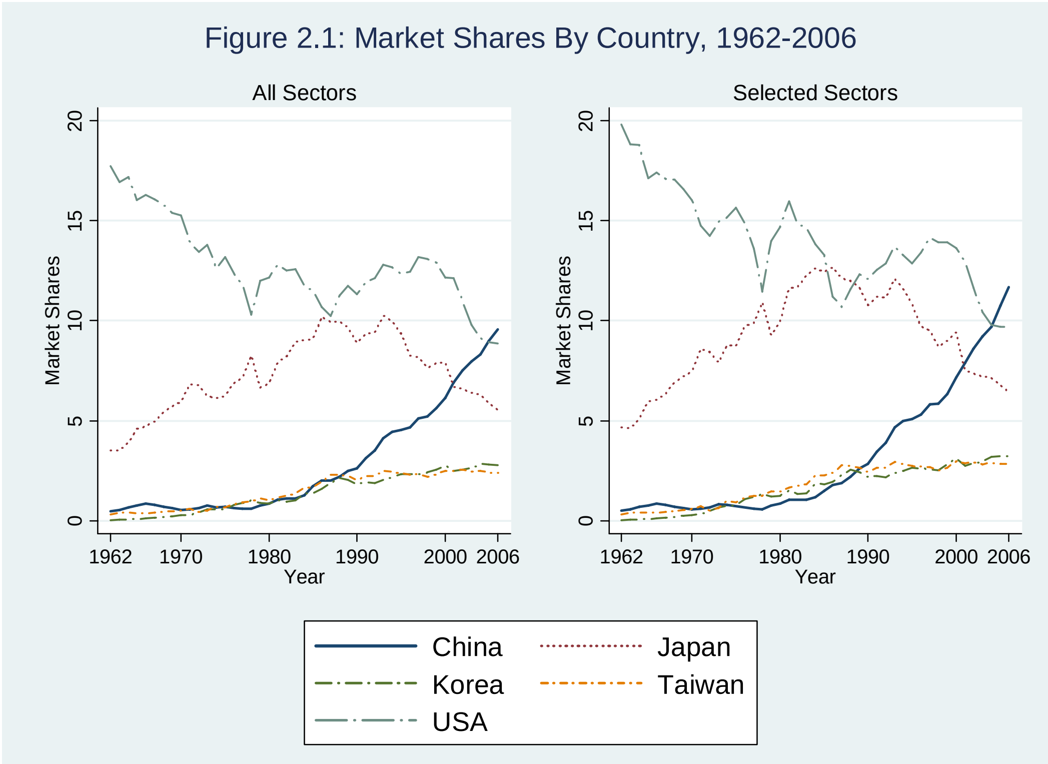

Figure 2.1: Market Shares By Country, 1962-2006
All Sectors
Selected Sectors
Market Shares
0
5
10
15
20
1962
1970
1980
1990
2000
2006
Year
China
Japan
Korea
Taiwan
USA

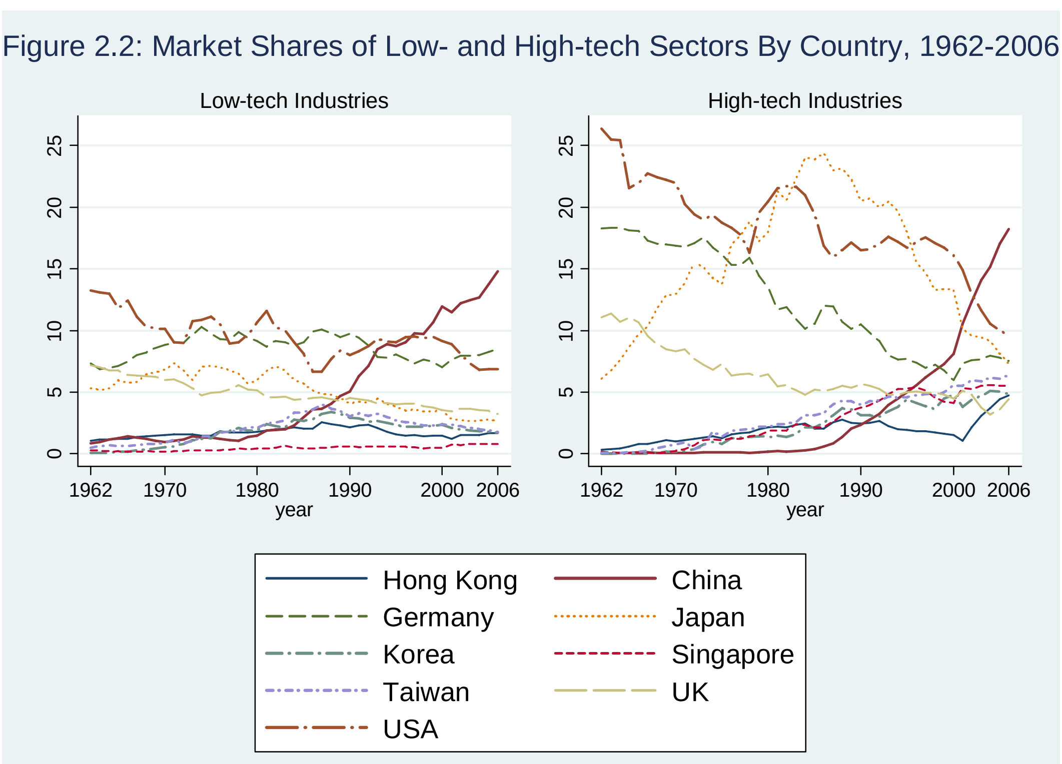

Figure 2.2: Market Shares of Low- and High-tech Sectors By Country, 1962-2006
Low-tech Industries
High-tech Industries
0
5
10
15
20
25
1962
1970
1980
1990
2000
2006
year
Hong Kong
China
Germany
Japan
Korea
Singapore
Taiwan
UK
USA

Figure 2.3: Market Shares of High-tech Sectors By Destination Markets, 1962-2006

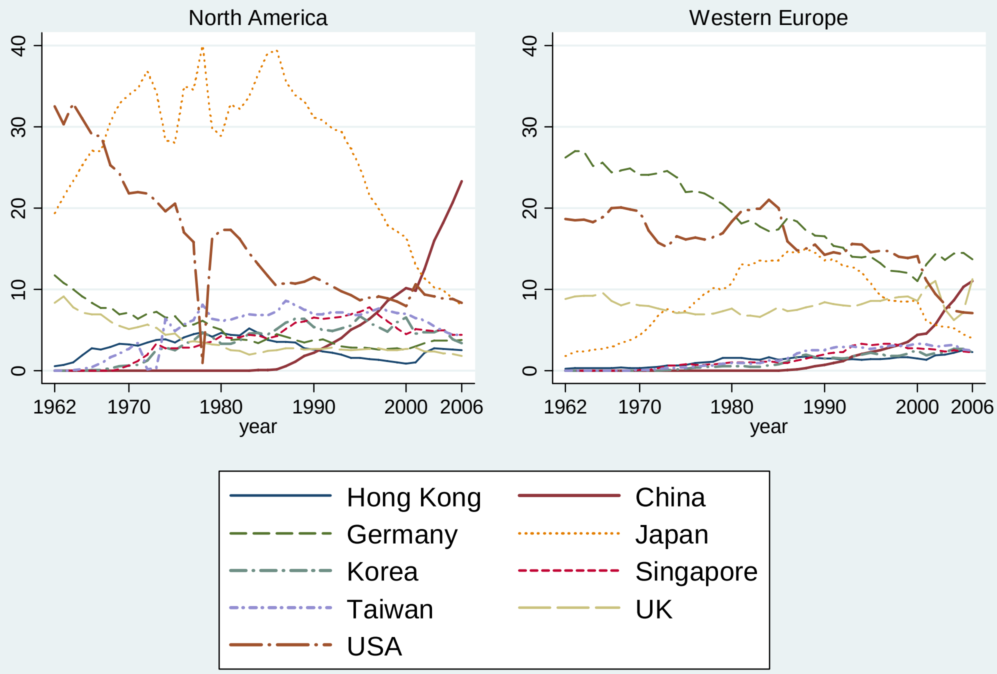

Figure 2.4: Reveal Comparative Advantage of High-tech Sectors

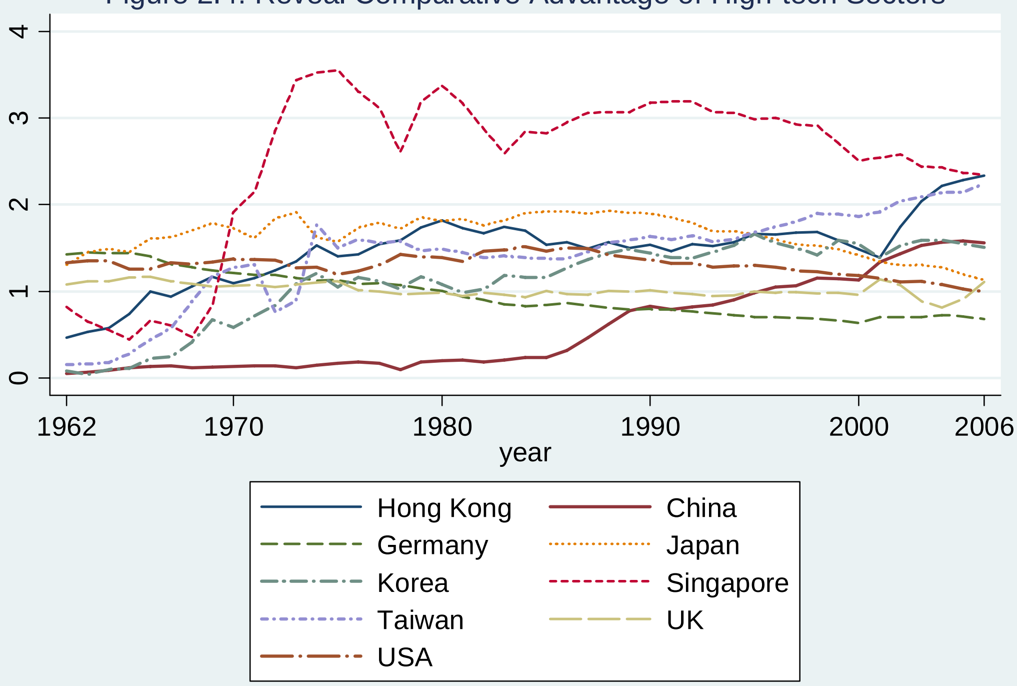

Table 2.1: China's Export Market Shares by Sector, 1962-2006, Period Average (%)

	1962-1969	1970-1979	1980-1989	1990-2000	2001-2006
Low-tech	***1.15***	***1.19***	***2.85***	***8.70***	***12.91***
Food, beverages and tobacco (FOD)	1.38	1.46	2.22	3.11	4.29
Textile, apparel and leather (TEX)	1.83	2.09	5.97	17.42	23.99
Wood and wood products (WOD)	0.48	0.60	1.19	6.00	12.83
Paper and paper products (PAP)	0.49	0.46	0.59	1.32	3.59
Non-metallic mineral products (MNM)	0.89	0.82	0.95	3.71	6.53
Basic metal industries (BMI)	0.43	0.23	0.57	2.18	5.45
Fabricated metal products (BMA)	0.47	0.68	1.62	7.22	13.20
Medium-tech	***0.15***	***0.19***	***0.41***	***1.17***	***3.37***
Chemical products (CHE)	0.39	0.45	0.97	1.77	3.81
Manufacture of agricultural and industrial machinery (MAI)	0.05	0.10	0.24	1.33	4.39
Manufacture of transport equipment (MTR)	0.03	0.05	0.09	0.50	2.10
High-tech	***0.08***	***0.10***	***0.63***	***5.07***	***14.56***
Professional and scientific equipment (MIO)	0.07	0.09	0.42	4.30	16.32
Manufacture of electrical machinery (MEL)	0.08	0.11	0.79	5.60	13.54

Table 2.2: China's Import Market Shares by Sector, 1962-2006, Period Average (%)

	1962-1969	1970-1979	1980-1989	1990-2000	2001-2006
Low-tech	***0.72***	***0.83***	***1.43***	***2.21***	***3.42***
Food, beverages and tobacco (FOD)	1.02	0.70	1.16	1.08	1.52
Textile, apparel and leather (TEX)	0.22	0.17	0.89	2.55	3.21
Wood and wood products (WOD)	0.01	0.00	0.78	1.35	0.90
Paper and paper products (PAP)	0.21	0.39	1.06	2.71	3.47
Non-metallic mineral products (MNM)	0.09	0.11	0.52	1.11	2.49
Basic metal industries (BMI)	1.10	2.46	3.68	4.29	8.25
Fabricated metal products (BMA)	0.16	0.32	0.57	1.34	2.51
Medium-tech	***0.51***	***0.62***	***1.59***	***2.89***	***4.82***
Chemical products (CHE)	1.10	0.84	1.86	3.22	6.15
Manufacture of agricultural and industrial machinery (MAI)	0.36	0.59	1.88	4.38	6.84
Manufacture of transport equipment (MTR)	0.14	0.46	1.09	1.26	1.83
High-tech	***0.26***	***0.19***	***1.03***	***2.47***	***9.33***
Professional and scientific equipment (MIO)	0.44	0.27	0.95	1.80	8.09
Manufacture of electrical machinery (MEL)	0.13	0.14	1.09	2.92	10.09

Table 2.3: China's Export Market Shares by Markets, 1962-2006, Period Average (%)

Region	1962-1969	1970-1979	1980-1989	1990-2000	2001-2006
All					
Africa	0.85	1.32	0.55	2.74	9.89
East Asia	7.80	5.46	7.95	14.05	18.54
Middle East	0.26	0.81	0.92	3.38	8.95
Oceania	0.66	0.89	1.35	5.13	6.56
Other America	0.03	0.08	0.25	1.58	4.85
Other Asia	1.71	1.60	1.90	5.50	15.27
Eastern Europe	0.03	0.08	1.04	1.93	4.15
North America	0.04	0.15	1.18	6.30	10.74
Japan	2.47	2.46	4.40	12.84	24.07
Western Europe	0.23	0.24	0.50	1.93	3.84
Low-tech Industries					
East Asia	12.91	10.58	16.17	26.43	25.12
Other Asia	2.86	2.42	2.25	6.58	20.69
North America	0.07	0.30	2.65	12.40	15.42
Japan	3.71	3.35	6.23	18.86	29.82
Medium-tech Industries					
East Asia	1.20	1.13	2.07	4.00	9.17
Other Asia	0.53	0.73	1.76	4.69	10.35
North America	0.00	0.04	0.19	0.94	2.78
Japan	0.54	1.01	1.94	4.20	11.30
High-tech Industries					
East Asia	0.92	0.56	3.18	10.68	19.50
Other Asia	0.63	0.86	1.32	4.64	16.51
North America	0.00	0.00	0.40	5.92	16.78
Japan	0.02	0.04	0.39	7.79	25.58

Table 2.4: Averages of Revealed Comparative Advantage in China, 1962-2006

	1962-1969	1970-1979	1980-1989	1990-2000	2001-2006
Low-tech	***1.65***	***1.76***	***1.88***	***1.74***	***1.35***
Food, beverages and tobacco (FOD)	1.96	2.15	1.51	0.65	0.45
Textile, apparel and leather (TEX)	2.63	3.07	3.95	3.50	2.51
Wood and wood products (WOD)	0.69	0.89	0.85	1.12	1.31
Paper and paper products (PAP)	0.70	0.67	0.43	0.26	0.37
Non-metallic mineral products (MNM)	1.30	1.21	0.68	0.73	0.67
Basic metal industries (BMI)	0.65	0.33	0.37	0.43	0.55
Fabricated metal products (BMA)	0.67	0.99	1.08	1.39	1.37
Medium-tech	***0.21***	***0.28***	***0.28***	***0.23***	***0.35***
Chemical products (CHE)	0.56	0.66	0.68	0.36	0.40
Manufacture of agricultural and industrial machinery (MAI)	0.07	0.15	0.15	0.26	0.45
Manufacture of transport equipment (MTR)	0.05	0.08	0.06	0.10	0.21
High-tech	***0.11***	***0.15***	***0.35***	***0.98***	***1.50***
Professional and scientific equipment (MIO)	0.10	0.14	0.25	0.79	1.67
Manufacture of electrical machinery (MEL)	0.12	0.16	0.42	1.11	1.40

Table 2.5: Export Similarity Index Between the Exports by China and Its Investing Countries Over Time

	1970	1980	1990	2000	2006
HK	0.49	0.63	0.78	0.88	0.77
Germany	0.35	0.41	0.46	0.48	0.55
Japan	0.43	0.31	0.38	0.53	0.58
Korea	0.56	0.76	0.77	0.64	0.67
Singapore	0.69	0.44	0.45	0.52	0.67
Taiwan	0.74	0.73	0.72	0.68	0.75
UK	0.42	0.47	0.48	0.56	0.68
USA	0.41	0.49	0.50	0.62	0.61

Table 2.6: Export Similarity Index Between China and Its Main Investing Countries With 10 Years Lag[1]

	1970	1980	1990	2000	2006
HK		0.61	0.85	0.85	0.82
Germany		0.40	0.44	0.48	0.55
Japan		**0.46**	**0.43**	**0.55**	**0.67**
Korea		**0.69**	**0.83**	**0.86**	**0.80**
Singapore		0.72	0.56	0.62	0.68
Taiwan		**0.81**	**0.85**	**0.88**	**0.88**
UK		0.47	0.47	0.51	0.61
USA		0.45	0.46	0.52	0.65

Note: The export similarity index is constructed by comparing China's exports with those of investing countries in 10 years earlier.

Table 2.7a: Effect of China's Exports on Its Investors' Exports Using Gravity Equation

	OLS	IV	FE	PPML
China's Exports (Log)	0.3254***	0.2114***	0.2421***	0.3689***
	(0.013)	(0.037)	(0.013)	(0.043)
Landlocked	-0.5364***	-0.6094***		0.0152
	(0.072)	(0.079)		(0.163)
Number of Islands	0.2823***	0.3071***		0.4447***
	(0.044)	(0.047)		(0.093)
Land Border	0.2294	0.1052		0.7075***
	(0.213)	(0.223)		(0.183)
Common Language	0.2571***	0.3249***		0.2202*
	(0.068)	(0.074)		(0.129)
Common Colonizer	0.1617	0.1977		0.7755***
	(0.125)	(0.134)		(0.293)
Common Country	0.1683	-0.1484		0.3794
	(0.119)	(0.172)		(0.394)
Ever Colony	0.6417***	0.6793***		0.1206
	(0.121)	(0.123)		(0.209)
Currently Colonized	0.1227	0.1420	-0.5037**	0.3081
	(0.159)	(0.178)	(0.256)	(0.403)
Product of Land Areas	-0.0156	-0.0303*		0.0618**
	(0.014)	(0.016)		(0.030)
Distance (Log)	-0.7550***	-0.8173***		-0.4438***
	(0.041)	(0.044)		(0.071)
Currency Union	0.6736***	0.7845***	0.2614**	0.0938
	(0.177)	(0.215)	(0.126)	(0.196)
Regional Trade Agreement	0.2913***	0.2758***	0.2919***	0.5015***
	(0.092)	(0.094)	(0.070)	(0.135)
GSP	-0.0027	0.0044	0.1990***	-0.2400*
	(0.095)	(0.096)	(0.076)	(0.140)
Importer GDP Per Capita (Log)	0.3168***	0.3162***	1.0193***	0.2741***
	(0.028)	(0.030)	(0.127)	(0.054)
Importer GDP (Log)	0.5366***	0.6552***	-0.2944**	0.4065***
	(0.025)	(0.041)	(0.138)	(0.069)
Exporter GDP Per Capita (Log)	0.7136***	0.6738***	2.1714***	0.5424**
	(0.077)	(0.083)	(0.362)	(0.228)
Exporter GDP (Log)	0.7107***	0.7557***	0.2064	0.4735***
	(0.037)	(0.040)	(0.274)	(0.078)
Year Fixed Effects	Y	Y	Y	Y
Country-pair Fixed Effects	N	N	Y	N
No. of Observations	32,229	32,229	32,229	32,229
R-squared	0.8272	0.8215	0.5982	0.9115

Table 2.7b: First Stage Estimation (IV Estimator): Determinants of China's Exports

	IV (GDP)
China's GDP (Log)	1.6259***
	(0.054)
Landlocked	-0.8357***
	(0.105)
Number of Islands	0.0125
	(0.124)
Land Border	-0.6353***
	(0.217)
Common Language	2.7863***
	(0.419)
Ever Colony	0.4560*
	(0.272)
Product of Land Areas	0.0020
	(0.029)
Distance (Log)	-1.1926***
	(0.094)
Regional Trade Agreement	-0.2773***
	(0.102)
GSP	0.0898
	(0.147)
Importer GDP Per Capita (Log)	0.1728***
	(0.047)
Importer GDP (Log)	0.8224***
	(0.033)
No. of Observations	32,693
R-squared	0.6355

Table 2.8: The Effect of China's Exports on Its Investing Countries' Exports Estimated from Cross-Sectional Analysis

	OLS	IV	PPML
1965	0.1850***	0.1046**	0.0319
	(0.038)	(0.050)	(0.042)
1970	0.1148***	0.1913***	-0.0100
	(0.025)	(0.049)	(0.025)
1975	0.2194***	0.2005***	0.1369***
	(0.028)	(0.035)	(0.030)
1980	0.2305***	0.1713***	0.2232***
	(0.024)	(0.033)	(0.043)
1985	0.3329***	0.2782***	0.3493***
	(0.035)	(0.037)	(0.046)
1990	0.4484***	0.1973***	0.3683***
	(0.031)	(0.063)	(0.041)
1995	0.4685***	0.3238***	0.4360***
	(0.032)	(0.053)	(0.040)
2000	0.5532***	0.3948***	0.4731***
	(0.032)	(0.064)	(0.054)
2005	0.5360***	0.3100***	0.4588***
	(0.036)	(0.059)	(0.060)

Table 2.9: Effect of China's Exports on Its Investing Countries' Exports By Period and By Averages of Period

	OLS	IV	FE	PPML
1962-1980	0.2016***	0.1858***	0.1506***	0.1143***
	(0.016)	(0.034)	(0.019)	(0.036)
1981-1990	0.3424***	0.2071***	0.2198***	0.3119***
	(0.019)	(0.036)	(0.022)	(0.041)
1991-2000	0.4492***	0.2665***	0.1909***	0.4197***
	(0.023)	(0.055)	(0.015)	(0.042)
2001-2006	0.4965***	0.3233***	0.1802***	0.5071***
	(0.027)	(0.058)	(0.026)	(0.061)
Decade Average	0.3243***	0.1376***	0.2631***	0.3652***
	(0.015)	(0.046)	(0.017)	(0.045)
Five-year Average	0.3339***	0.1719***	0.2749***	0.3615***
	(0.015)	(0.041)	(0.016)	(0.042)

Table 2.10: Effects of China's Exports on Its Investing Countries' Exports by Tech Intensity

	OLS	IV	FE	PPML
All Years				
Low-tech Sectors	0.2604***	0.1932***	0.1759***	0.3267***
	(0.013)	(0.041)	(0.014)	(0.052)
Medium-tech Sectors	0.2609***	0.1630***	0.1282***	0.3209***
	(0.019)	(0.054)	(0.013)	(0.048)
High-tech Sectors	0.3272***	0.3546***	0.1875***	0.4143***
	(0.014)	(0.035)	(0.013)	(0.039)
1991-2000				
Low-tech Sectors	0.3459***	0.2024***	0.1335***	0.3908***
	(0.021)	(0.065)	(0.018)	(0.053)
Medium-tech Sectors	0.3475***	0.0566	0.0939***	0.4285***
	(0.031)	(0.067)	(0.015)	(0.048)
High-tech Sectors	0.4193***	0.4965***	0.1462***	0.4646***
	(0.022)	(0.064)	(0.016)	(0.046)
2001-2006				
Low-tech Sectors	0.3972***	0.1519*	0.1166***	0.4668***
	(0.033)	(0.088)	(0.029)	(0.065)
Medium-tech Sectors	0.4044***	0.3925***	-0.0019	0.4494***
	(0.034)	(0.076)	(0.030)	(0.073)
High-tech Sectors	0.4058***	0.3527***	0.1244***	0.6127***
	(0.027)	(0.054)	(0.027)	(0.051)

Table 2.11: Effects of China's Exports on Its Investing Countries by Investing Countries and Tech Intensity

	OLS	IV	FE	PPML
All Sectors				
Western Investors	0.1762***	0.2219***	0.1165***	0.2988***
	(0.015)	(0.050)	(0.012)	(0.048)
Japan	0.2864***	0.2434*	0.1483***	0.4924***
	(0.040)	(0.139)	(0.023)	(0.064)
Four Asian Tigers	0.4697***	0.5850***	0.3608***	0.5515***
	(0.021)	(0.076)	(0.022)	(0.060)
Korea and Taiwan	0.4449***	0.4929***	0.3525***	0.6505***
	(0.032)	(0.119)	(0.031)	(0.070)
Low-tech Sectors				
Western Investors	0.1417***	0.1548***	0.1031***	0.2525***
	(0.014)	(0.051)	(0.012)	(0.048)
Japan	0.2426***	0.3031**	0.1162***	0.3751***
	(0.036)	(0.151)	(0.026)	(0.073)
Four Asian Tigers	0.3741***	0.3053***	0.2591***	0.5188***
	(0.021)	(0.090)	(0.025)	(0.071)
Korea and Taiwan	0.3868***	0.3782***	0.3006***	0.5762***
	(0.030)	(0.120)	(0.037)	(0.051)
High-tech Sectors				
Western Investors	0.2241***	0.3642***	0.1210***	0.3478***
	(0.018)	(0.052)	(0.012)	(0.040)
Japan	0.3815***	0.3424***	0.2536***	0.3953***
	(0.034)	(0.111)	(0.030)	(0.058)
Four Asian Tigers	0.4170***	0.5721***	0.2254***	0.5114***
	(0.021)	(0.063)	(0.024)	(0.045)
Korea and Taiwan	0.3604***	0.4147***	0.1829***	0.5723***
	(0.028)	(0.091)	(0.029)	(0.056)

Table 2.12: Effects of China's Exports on Its Investing Countries' Exports By the Income of the Destination Markets

	OLS	IV	FE	PPML
High-income	0.3129***	0.3650***	0.1872***	0.3420***
	(0.027)	(0.038)	(0.025)	(0.048)
Mid-income	0.3364***	-0.1497	0.2788***	0.3316***
	(0.027)	(0.124)	(0.024)	(0.073)
Low-income	0.2771***	0.1105	0.2288***	0.4622***
	(0.023)	(0.099)	(0.024)	(0.058)
Least-income	0.3423***	0.2140	0.2900***	0.3784***
	(0.035)	(0.135)	(0.027)	(0.045)
Low-tech Sector				
Low-income	0.1935***	0.1601*	0.1663***	0.3756***
	(0.025)	(0.095)	(0.027)	(0.057)
Least-income	0.1657***	-0.0263	0.1375***	0.0777
	(0.031)	(0.137)	(0.037)	(0.071)
High-tech Sector				
High-income	0.3619***	0.4466***	0.1464***	0.3647***
	(0.021)	(0.039)	(0.024)	(0.040)

Table 2.13: Dynamic Effects of China's Exports

	OLS	IV	FE	PPML
China's Exports (t)	0.3254***	0.2114***	0.2421***	0.3689***
	(0.013)	(0.037)	(0.013)	(0.043)
China's Exports (t-1)	0.3004***	0.1871***	0.1974***	0.0264***
	(0.013)	(0.039)	(0.012)	(0.001)
China's Exports (t-3)	0.2668***	0.1931***	0.1481***	0.0227***
	(0.013)	(0.038)	(0.010)	(0.001)
China's Exports (t-5)	0.2335***	0.1875***	0.1085***	0.0193***
	(0.012)	(0.038)	(0.009)	(0.001)

Table 2.14: Effect of Burundi's Exports on the Exports by China's Investing Countries Using Gravity Equation

	OLS	IV	FE	PPML
Burundi's Exports (Log)	0.0587***	-0.1424***	0.0155***	-0.0245**
	(0.012)	(0.048)	(0.004)	(0.012)
Landlocked	-0.8428***	-0.4913***		-0.2665
	(0.086)	(0.115)		(0.195)
Number of Islands	0.5398***	0.3040***		0.5221***
	(0.054)	(0.086)		(0.087)
Land Border	-0.2481	0.2149		0.6277***
	(0.237)	(0.206)		(0.184)
Common Language	0.5133***	0.4843***		0.3919**
	(0.086)	(0.112)		(0.177)
Common Colonizer	0.3308**	0.3264		0.7672*
	(0.161)	(0.287)		(0.436)
Common Country	-0.8141***	-1.4726***		-0.6651***
	(0.156)	(0.282)		(0.228)
Ever Colony	0.8860***	0.5886***		0.1344
	(0.156)	(0.191)		(0.208)
Currently Colonized	0.1497	1.0555***	-0.3013	0.6495***
	(0.204)	(0.246)	(0.421)	(0.245)
Product of Land Areas	-0.0115	-0.0278		-0.0081
	(0.020)	(0.034)		(0.048)
Distance (Log)	-0.9694***	-0.7641***		-0.5208***
	(0.051)	(0.067)		(0.073)
Currency Union	1.0862***	0.2579	0.4044***	-0.0580
	(0.268)	(0.213)	(0.132)	(0.204)
Regional Trade Agreement	0.2760**	0.3977**	0.2896***	0.3810***
	(0.108)	(0.156)	(0.080)	(0.132)
GSP	-0.1538*	0.2762*	0.0874	-0.1372
	(0.090)	(0.155)	(0.073)	(0.130)
Importer GDP Per Capita (Log)	0.3207***	0.4966***	1.1637***	0.3773***
	(0.035)	(0.048)	(0.139)	(0.061)
Importer GDP (Log)	0.8169***	0.9798***	0.0868	0.8573***
	(0.025)	(0.059)	(0.151)	(0.046)
Exporter GDP Per Capita (Log)	0.8762***	1.1020***	3.3568***	0.5664**
	(0.099)	(0.148)	(0.427)	(0.237)
Exporter GDP (Log)	0.6814***	0.7003***	-0.7587**	0.6094***
	(0.050)	(0.077)	(0.318)	(0.109)
Year Fixed Effects	Y	Y	Y	Y
Country-pair Fixed Effects	N	N	Y	N
No. of Observations	42,426	8,107	42,426	42,426
R-squared	0.7558	0.8381	0.4543	0.8943

Appendix II

Appendix Table 2.1: Distribution of China's FDI Flows By Sources (%)

	1997	1998	1999	2000	2001	2002	2003	2004	2005
Asia	**75.74**	**68.92**	**66.55**	**62.59**	**63.17**	**61.75**	**63.74**	**62.05**	**59.21**
Hong Kong	45.59	40.71	40.58	38.07	35.66	33.86	33.08	31.33	29.75
Japan	9.56	7.48	7.37	7.16	9.28	7.94	9.45	8.99	10.82
Korea	4.73	3.97	3.16	3.66	4.59	5.16	8.39	10.30	8.57
Singapore	5.76	7.49	6.55	5.34	4.57	4.43	3.85	3.31	3.65
Taiwan	7.27	6.41	6.45	5.64	6.36	7.53	6.31	5.14	3.57
Western Hemisphere									
Virgin Islands	3.79	8.87	6.59	9.41	10.76	11.60	10.80	11.10	14.96
Cayman Islands	0.35	0.71	0.94	1.53	2.28	2.24	1.62	3.37	3.23
Pacific Islands									
Samoa	0.41	0.28	0.50	0.70	1.16	1.67	1.84	1.86	2.24
United States	**7.16**	**8.58**	**10.46**	**10.77**	**9.46**	**10.28**	**7.85**	**6.50**	**5.07**
Europe	**9.81**	**9.48**	**11.90**	**11.70**	**9.57**	**7.68**	**7.98**	**7.91**	**9.35**
Germany	2.19	1.62	3.41	2.56	2.59	1.76	1.60	1.75	2.54
United Kingdom	4.10	2.58	2.59	2.86	2.24	1.70	1.39	1.31	1.60

Source: China’s Statistical Yearbook (1998-2006).

Appendix Table 2.2: Product Classification by Technology Intensity

Sectors	Description	Tech-Intensity	SITC Rev. 2
FOD	Food, beverages, and tobacco	Low-tech	00-09, 11-12
TEX	Textile, leather apparel and leather industries	Low-tech	61, 65, 83-85, 89
WOD	Wood and wood products, including furniture	Low-tech	63, 82
PAP	Paper and paper products, printing and publishing	Low-tech	64
MNM	Non-metallic mineral products, etc	Low-tech	66
BMI	Basic metal industries	Low-tech	67, 68
BMA	Fabricated metal products, except machinery and transport equipment	Low-tech	69, 81
CHE	Chemical products, rubber and plastic products	Medium-tech	51-59, 62
MAI	Manufacture of agricultural and industrial machinery, except electrical machinery	Medium-tech	71-74
MTR	Manufacture of transport equipment	Medium-tech	78, 79
MIO	Professional, scientific, measuring and controlling equipment n.e.c., photographic and opitcal goods, office and data processing machines	High-tech	75, 87, 88
MEL	Manufacture of electrical machinery, apparatus, appliances and supplies	High-tech	76, 77

Source: The classification follows ECB (2005) with minor revision.

Appendix Table 2.3: Geographic Grouping of Importing Economies

Africa	South Africa	Papua N.Guinea	Suriname	Romania
Algeria	Sudan	Solomon Islands	Trinidad & Tobago	Slovenia
Angola	Swaziland	Samoa	Turks & Caicos Islands	Azerbaijan
Benin	Tanzania	Cook Islands	Uruguay	Macedonia
Botswana	Togo	Tonga	Venezuela	Armenia
Burkina Faso	Tunisia	Tuvalu	Aruba	Moldova
Burundi	Uganda	Vanuatu	French Guiana	Belarus
Cameroon	Western Sahara	Marshall Islands	Grenada	Faeroe Islands
Cape Verde	Zambia	Micronesia	British Virgin Islands	**North America**
Central African Republic	Zimbabwe	French Polynesia	Antigua & Barbuda	United States
Chad	**East Asia**	Nauru	Montserrat	Canada
Comoros	Hong Kong	Norfolk Islands	**Other Asia**	**Japan**
Congo	Indonesia	Wallis and Futuna Islands	Bangladesh	**Western Europe**
Congo, Dem. Rep. of (Zaire)	Korea, South	**Other America**	Bhutan	Austria
Cote Divoire	Malaysia	Argentina	India	Belgium-Lux
Djibouti	Philippines	Bahamas	Korea, North	Cyprus
Egypt	Singapore	Barbados	Maldives	Denmark
Equatorial Guinea	Taiwan	Belize	Mongolia	Finland
Eritrea	Thailand	Bermuda	Nepal	France
Ethiopia	Macao	Bolivia	Pakistan	Germany
Gabon	Brunei Darussalam	Brazil	Sri Lanka	Greece
Gambia	Cambodia	Cayman Islands	Kazakhstan	Ireland
Ghana	Lao People's Dem. Rep.	Chile	Uzbekistan	Italy
Guinea	Myanmar	Colombia	Kyrgyzstan	Malta
Guinea-Bissau	Viet Nam	Costa Rica	Turkmenistan	Netherlands
Kenya	**Middle East**	Cuba	Tajikistan	Portugal
Lesotho	Afghanistan	Dominican Rep.	Timor-Leste	Spain
Liberia	Bahrain	Dominica	Palau	Sweden
Libya	Yemen	Ecuador	**Eastern Europe**	United Kingdom
Madagascar	Iran	El Salvador	Iceland	Norway
Malawi	Iraq	Greenland	Albania	Switzerland
Mali	Israel	Guadeloupe	Russia	Gibraltar
Mauritania	Jordan	Guatemala	Croatia	Malta
Mauritius	Kuwait	Guyana	Bosnia Herzg	Andorra
Mayotte	Lebanon	Haiti	Serbia	**China**
Morocco	Oman	Honduras	Turkey	
Mozambique	Qatar	Jamaica	Ukraine	
Namibia	Saudi Arabia	Mexico	Georgia	
Niger	Syria	Netherland Antilles	Bulgaria	
Nigeria	United Arab Emirates	Nicaragua	Czechoslovak	
Rwanda	**Oceania**	Panama	Hungary	
Sao Tome and Principe	Australia	Paraguay	Slovakia	
Senegal	Fiji	Peru	Estonia	
Seychelles	Kiribati	St. Kitts & Nevis	Latvia	
Sierra Leone	New Calednia	St. Vincent & Gren.	Lithuania	
Somalia	New Zealand	St. Lucia	Poland	

Appendix Table 2.4: Descriptive Statistics of Variables

Variables	Mean	Std. Dev.	Min	Max
Landlocked	0.15	0.36	0	1
Number of Islands	0.49	0.59	0	2
Land Border	0.01	0.11	0	1
Common Language	0.22	0.42	0	1
Common Colonizer	0.06	0.24	0	1
Common Country	0.00	0.03	0	1
Ever Colony	0.05	0.23	0	1
Currently Colonized	0.02	0.14	0	1
Product of Land Areas (Log)	23.41	3.71	10.55	32.73
Distance (Log)	8.42	0.69	5.15	9.42
Current Union	0.00	0.05	0	1
Regional Trade Agreement	0.03	0.16	0	1
GSP	0.88	0.33	0	1
Log GDP per capita of Importers	8.58	1.16	5.03	11.58
Log GDP of Importers	17.45	2.02	11.46	23.27
Log GDP per capita of Exporters	9.73	0.67	7.45	10.66
Log GDP of Exporters	20.26	1.78	15.86	23.27
CPI	107.76	56.90	30.20	201.60
Product of Land Areas of China and Importers (Log)	28.06	2.27	20.15	32.73
Distance of China and Importers (Log)	8.46	0.56	6.63	9.39
Log GDP per capita of China	7.65	0.76	6.43	8.87
Log GDP of China	21.54	0.94	19.82	22.96
Directional Exports from China (Log)	10.63	2.99	-0.44	19.11
Directional Exports (Log)	11.11	2.93	-0.42	19.14
Directional Exports of Low-tech Sectors (Log)	10.10	2.78	-2.48	17.89
Directional Exports of Medium-tech Sectors (Log)	10.13	3.15	-4.50	18.52
Directional Exports of High-tech Sectors (Log)	9.42	3.08	-3.40	18.35
Directional Exports of Low-tech Sectors from China (Log)	10.48	2.76	1.31	18.28
Directional Exports of Medium-tech Sectors from China (Log)	9.20	2.72	-1.28	17.08
Directional Exports of High-tech Sectors from China (Log)	8.56	3.11	-1.48	18.39

Appendix Table 2.5: The Effects of China's Exports on Its Investors' Exports: Robustness Check

China's Exports (Log)	0.6717***	0.7923***
	(0.025)	(0.027)
Landlocked	-0.0712	-0.1907
	(0.324)	(0.370)
Number of Islands	-0.0943	0.2790***
	(0.137)	(0.040)
Land Border	-0.0594	0.1688
	(0.200)	(0.190)
Common Language	0.0420	0.0320
	(0.065)	(0.060)
Common Colonizer	0.2464**	0.1478
	(0.100)	(0.100)
Common Country	0.2444	0.2636
	(0.366)	(0.359)
Ever Colony	0.7364***	0.5170***
	(0.118)	(0.109)
Currently Colonized	0.1983	0.1463
	(0.160)	(0.162)
Product of Land Areas	-1.2829	-0.1143***
	(1.095)	(0.030)
Distance (Log)	-0.9530***	-0.8956***
	(0.034)	(0.034)
Currency Union	-0.2286	-0.0943
	(0.330)	(0.315)
Regional Trade Agreement	-0.0278	-0.0974
	(0.102)	(0.107)
GSP	0.0511	0.0860
	(0.073)	(0.081)
Importer GDP Per Capita (Log)	0.0000	0.0000
	(0.000)	(0.000)
Importer GDP (Log)	0.0000	0.0000
	(0.000)	(0.000)
Exporter GDP Per Capita (Log)	0.9136	0.4675***
	(0.910)	(0.087)
Exporter GDP (Log)	2.6310	0.8621***
	(1.702)	(0.063)
Exporter-year fixed effects	Y	N
Importer-year fixed effects	Y	Y
No. of Observations	32,229	32,229
R-squared	0.9218	0.9061

Part III:

The Sensitivity of Matched Sampling Methodology in the Literature on Foreign Acquisition

3.1 Introduction

One of the important questions in the literature of foreign direct investment (FDI) is to investigate whether and why foreign-owned plants have superior characteristics. For example, they are more productive, hire more employees and pay higher wages than domestically-owned plants[31]. This question has potentially important implications since many governments in developing countries encourage the entrance of foreign firms in an attempt to promote technology transfer, create new jobs in the industrial sector, and boost domestic wage level. However, the direction of causality between foreign ownership and the associated superior characteristics remains unclear. If foreign investment gravitates towards more productive plants, then the observed correlation between foreign ownership and the superior characteristics will overstate the positive impact of foreign investment. A range of econometric techniques have been applied to resolve the identification problem. Among them, the combination of difference-in-differences (DD) estimation with propensity score matching has become a trendy methodology in the related literature. It is borrowed from the program evaluation literature where similar problem of reverse causality exists. The fundamental idea is to resolve the issue of sample selection (better plants are acquired by foreigners, "cherry-picking") through randomization.

In answering whether foreign acquisition could actually result in superior plant characteristics, the ideal experiment would randomly assign a set of plants in the pool of domestic-owned plants to become foreign-owned at a certain time. This randomization ensures a complete balancing of all relevant observable and unobservable characteristics between plants

[31] For foreign direct investment (FDI) and employment, see, for example, Lipsey, Sjöholm, and Sun (2010), Bandick and Karpaty (2007), Bandick and Görg (2010), Gong, Görg, and Maioli (2007). For FDI and wages, refer to Aitken, Harrison, and Lipsey (1996), Lipsey and Sjöholm (2004), Sjöholm and Lipsey (2006), and Huttunen (2007). For FDI and productivity, Lipsey and Sjöholm (2005) gave an excellent survey on this issue. Lipsey (2004) summarized literature on host country effects of FDI in general.

with and without foreign ownership. As a result, the potentially confounding factors are independent of foreign acquisition. If plants with and without foreign ownership are identical otherwise, then the mean difference in the variables of interest, such as employment growth, can reveal the effects of foreign ownership. Unfortunately, in reality foreign ownership cannot be assigned randomly and differ across plants in terms of timing. A matching technique is thus employed to establish counterfactuals by finding controls (plants without foreign ownership) that are as similar to the treated (plants that are acquired by foreigners) as possible. Specifically, the identifying assumption for the matching technique is that, conditional on all relevant observable covariates Z, the potential outcomes are independent of treatment (conditional independence) so treatment status is random. Dehejia and Wahba (2002) revealed that matching estimator works well in alleviating the bias due to systematic differences between the treated and comparison units. The substantial differences between plants with and without foreign ownership seemingly provide a venue to apply matching estimator. However, to my best knowledge, no sensitivity study has been carried out in the literature of foreign acquisition. This paper fills the gap in testing the robustness of the matching estimator in case of foreign acquisition.

This paper investigates the robustness of matching estimator for foreign acquisition from two perspectives. First, within matching estimators, I experiment with different matching methodologies to examine the robustness of the results. Second, I use the conventional panel data methods to evaluate whether the estimates are robust.

The data I use for the research is Annual Manufacturing Survey data from Indonesian Statistical Office for the period of 1975 to 2005. The data have a wide range of variables including input, output, electricity consumption, etc., which makes it possible to balance the relevant pre-foreign acquisition variables. The issue I study for the sensitivity of the matched estimator is whether foreign acquisition boosts employment growth. In particular, employment growth is chosen as the outcome variable since it is a real production variable with less measurement problems and carries significant policy implications.

My results show that, in the estimation of employment growth effects of foreign acquisition, the results from the matching procedure are not sensitive to the choice of matching methods or to the choice of the parameters involved in each matching method if balancing property is satisfied. When compared with the results from other conventional panel data methods, the matching estimates are closer to the fixed effect estimate and Arellano-Bond GMM estimate.

The remainder of the paper is structured as follows. Section 3.2 discusses the matching methodology and answers why it is necessary. Section 3.3 describes the data used. Section 3.4 presents the benchmark matching estimator and section 3.5 shows the estimation results from the traditional panel data estimator, while section 3.6 compares the estimates of the employment growth dynamics using matching and other methodologies. Section 3.7 concludes.

3.2 Matched Sampling Methodology

3.2.1 The Evaluation Problem

Foreign acquisition can be considered as a treatment that possibly brings about a change in employment growth or changes in other variables of interest in general, compared to some baseline, called the control. The basic problem in identifying such a causal effect is that employment growth is observed under either the treatment or control regimes, but never both. This is analogous to the evaluation of the effectiveness of a program. In the program evaluation literature, the effect of foreign acquisition is often estimated via the average treatment (foreign acquisition) effect on the treated (domestic plants acquired by foreigners), defined as:

$$ATT = E\left(Y_{1,t} - Y_{0,t} \middle| X\right) = E\left(Y_{1,t} \middle| X\right) - E\left(Y_{0,t} \middle| X\right) \tag{3.1}$$

where Y is the variable of interest, employment growth in this case. $Y_{1,t}$ is the employment growth rate for a plant that is acquired by foreigners in year t after foreign acquisition, where $Y_{0,t}$ is the employment growth rate for the same plant had it not been acquired by foreigners in the same year. X denotes the vector of observed plant characteristics. LaLonde (1986) and Dehejia and Wahba (1999, 2002) used this specification to study the effect of a labor training program, National Supported Work (NSW), on the postintervention earnings. Yasar and Paul (2008) employed the same specification to study the productivity effects of foreign contact for three Turkish manufacturing industries.

Although Dehejia and Wahba's (1999, 2002) found that the above average treatment effect can lower bias, Smith and Todd (2005) concluded that the difference-in-differences matching estimator performs the best among the estimators they study since the time-invariant bias is differenced out. This is consistent with the findings of Heckman, Ichimura and Todd (1997) and Heckman, Ichimura, Smith and Todd (1998). This partly explains why the combination of propensity score matching and difference-in-differences (DD) estimator has been widely adopted in the literature of foreign acquisition[32]. It exploits the time variation in panel data and allows for the existence of unobserved time-invariant factors that affect the selection. In contrast, the average treatment effect estimator makes use of the cross-sectional differences and

[32] See, for example, Huttunen (2007), Arnold and Javorcik (2009), Lipsey, Sjöholm and Sun (2010), Bandick and Görg (2010).

compares the outcome of the foreign-owned plants with that of the matched domestically owned plants only in the post-acquisition period. The DD estimator is defined in the following way:

$$DD = \left(E(Y_{1,t} \mid X) - E(Y_{1,t-1} \mid X)\right) - \left(E\left(Y_{0,t} \middle| X\right) - E\left(Y_{0,t-1} \middle| X\right)\right) \tag{3.2}$$

The notation is similarly specified as in equation (1). $t-1$ refers to one year before foreign acquisition[33]. This is first proposed in Arnold and Javorcik (2009) and Huttunen (2007), and later used in Lipsey, Sjöholm and Sun (2010).

The causal inference relies on the representation of counterfactuals in the last term of (2)—the change in employment growth rate a treated (foreign-owned) plant would have had if it was untreated (domestically-owned). This is estimated using the outcomes for untreated plants. To resolve the sample selection bias due to the systematic difference in the distribution of plant characteristics between plants with and without foreign ownership, a matched control plant is found or constructed so that it shares similar plant characteristics as the treated one. Built on the assumption that, conditioning on the observed plant characteristics, the treated and the control do not systematically differ from each other, this essentially "randomizes" the treatment (foreign acquisition) of plants, such that selection of treated plants is uncorrelated with both observable and unobservable characteristics.

To estimate the model in (2), a matched control group needs to be constructed to represent the counterfactual. Propensity score matching is employed, as will be discussed in more detail in the following section. The results from the estimation are presented in section 3.4.

[33] When the average of the outcome variable in all the years before treatment (foreign acquisition) is used, the results remain robust.

Additionally, the paper tests the sensitivity of the results to the choice of matching methodologies.

3.2.2 Propensity Score Matching

To resolve the dimensionality problem in matching on a vector of plant characteristics between foreign-owned plants and domestically-owned plants, Rosenbaum and Rubin (1983) proposed to use propensity scores which encompass all the plant characteristics that are deemed to be important both for the probability of being acquired by foreigners and for improving employment growth. The composite score is estimated using a probit model. Then it can be used to match the treated and control plants using a number of matching methods.

Among the matching methods, nearest neighbor matching is widely used in the related literature. Nearest neighbor matching selects the domestic plant whose propensity score is closest to the foreign-owned one. This method has the advantage of finding each foreign-owned plant a matched domestically-owned plant. However, it potentially allows for a “bad” match when the propensity score of the closest control plant is still far from that of the foreign-owned plant. To avoid such cases, caliper matching is utilized, which imposes the maximum distance between the propensity score of the domestically-owned plant and of the foreign-owned plant. When there are multiple (no) good matches available, this method allows for the use of extra (fewer) units. Another widely used matching method is kernel method. Kernel method constructs a match for each foreign-owned plant using a kernel-weighted average over all control plants. The weights depend on the distance between each comparison group observation and the corresponding treated observation. The kernel matching method uses the pool of domestically-owned plants in constructing the estimated counterfactual outcome and has the advantage of a reduction in the asymptotic mean squared error (Heckman, Ichimura and Todd 1997, 1998, and Heckman, Ichimura, Smith and Todd 1998).

Each matching method balances between bias reduction and precision improvement. For example, the caliper matching reduces the bias of the estimates since it imposes the maximum distance between the matched pair, but it decreases the precision of the estimates at the same time because foreign-owned plants that cannot find matched control plants within the caliper are dropped. In addition, there are several other parameters that could potentially affect the results. Among them is the choice of the number of the controlled plants. In the nearest neighbor matching, for instance, the domestically-owned plants in the matched pair could be either the one that is closest to the foreign-owned plant or the average of the multiple closest control plants. The paper tests the sensitivity of the results to these parameters.

3.3 The Data

The Indonesian manufacturing data are supplied by the Indonesian Statistical Office for the period, 1975 to 2005 for all manufacturing plants with more than 20 employees. The dataset contains a comprehensive set of variables concerning plant characteristics such as ownership, employment, value added, input, etc. This rich information makes it possible to carry out the matching technique in the paper.

Is matching necessary in the study of foreign acquisition? The answer is yes. Much of the literature documents that foreign-owned plants are systematically different from domestically-owned plants. This is one of the reasons why propensity score matching is becoming popular in the related literature since it balances the relevant pre-acquisition plant characteristics. The standard linear regression assumes the same linear relationship on all the explanatory variables for all observations, which is equivalent to putting the same weight on domestically-owned plants and on foreign-owned plants. The confounding variable bias could be reduced through matching methods.

I first summarize the data to demonstrate the systematic difference between foreign-owned and domestically-owned plants. I use the benchmark empirical model from Lipsey, Sjöholm, and Sun (2010) to study how foreign acquisition affects employment growth. The observed plant characteristics that are controlled for include plant size measured by employment, input of intermediate goods, energy intensity, and labor productivity proxied by value added per employee. Figure 3.1 presents the visual evidence regarding the different distributions of plant characteristics by ownership. Specifically, Figure 3.1 plots the histogram on each plant characteristics for each type of ownership and the fitted curve gives the kernel density estimate of the distribution. The distribution of the plant characteristics for foreign-owned plants shifts rightward comparing to the distribution for domestically-owned plants. Among them, the distribution of employment for foreign-owned plants is substantially different from that for the domestically-owned plants and the distributions of other plant characteristics for foreign-owned plants have different variation from those for domestically-owned plants. Table 3.1 demonstrates that, although there are some variations in magnitude across industries, foreign-owned plants, in general, are bigger, more productive, more energy-intensive, and uses more intermediate goods for production.

Whatever matching method is chosen to obtain a matched sample, a composite score is needed to summarize the relevant plant characteristics. I use a probit model to obtain the propensity score, modeling the propensity for a domestic plant to be acquired by foreigner. The model specification is similar to that in Lipsey, Sjöholm and Sun (2010), and Table 3.2 gives the results[34].

Next I use a number of matching techniques to construct the matched sample of plants. It is worth noting that the matched pairs are from the same year and same industry regardless of the matching technique used. The main criterion for constructing a matched sample is that foreign-owned plants and the matched domestically-owned plants have similar pre-acquisition values on the control variables. Table 3.3 tabulates the balancing test results for two matching techniques. In the matched sample, the t statistics in comparison of the means of the control variables are either insignificant or much smaller in magnitude after matching. Figure 3.2 and Figure 3.3 give the visual evidence by plotting the histogram of the distribution on plant characteristics after matching and the fitted curve is the kernel density estimate of the distribution. They illustrate that the distributions of the plant characteristics between foreign-owned and domestically-owned plants are more similar in the two matched samples.

3.4 Matching Estimators

After constructing the matched samples, I now estimate the employment growth effect of foreign acquisition as specified in model (2). The results are shown in Table 3.4. Each column

[34] The results presented in this paper are based on the propensity scores obtained by fitting the probit model in one period before foreign acquisition. If three-year average or five-year average is used instead, the results remain robust.

gives the estimation results when different outcome variables are defined. A variety of matching techniques with diversifying parameters specified are experimented.

The first two columns present the results when 3-year/5-year average employment growth rate is the variable of interest. The results should be similar to the OLS results which often give the average effects of foreign acquisition in all the years following acquisition[35]. The employment growth effect of foreign acquisition is large across different matching techniques. For example, when the nearest neighbor matching is employed with only one control for each treated, the employment growth rate is estimated to be, on average, almost 16% (since exp(0.147)-1=0.158) higher after foreign acquisition. The results are robust to the choice of number of controls.

One advantage of DD estimator is that it allows for the estimation of the employment growth path following foreign acquisition. The last three columns tabulate the results for the year of acquisition, one year after and two years after. The results show that employment growth effects of foreign acquisition mainly concentrates on the year of acquisition. In the nearest neighbor matching with one control, the estimated employment growth effect in the year of acquisition is as large as 35% (since exp(0.297)-1)=0.346). However, in the next two years, foreign acquisition has a negligible effect on employment growth. Again the results remain robust to different matching procedures with various parameters.

The caliper matching procedure is a modified version of the nearest neighbor with one control in this research. The modification is the imposition of the maximum distance between the treated and the control for each pair. The foreign-owned plants whose closest match is not within

[35] If the post-acquisition period could be defined by three-year or five-year periods, the OLS should yield similar results. However, it is not possible to define the post-acquisition period for domestically-owned plants in unmatched samples. If the unmatched sample uses all the domestically-owned plants and foreign acquired plants with different post-acquisition periods only, OLS results are similar to the estimates when the whole unmatched sample (without restricting the number of years in post-acquisition period) is used, as in Table 3.5.

the specified caliper are dropped. When comparing the estimation results from caliper matching to the results from the nearest neighbor matching with one control, the difference is sensitive to the choice of caliper. If the caliper is as small as 0.00001, the number of foreign-owned plants in the matched sample drops from 386 to 225. The caliper matching sample supposedly contains matched pairs that are more similar to each other compared to those in the nearest neighbor matching. Thus it should give an estimate potentially with less bias. For the three year average, when a caliper is imposed and the number of matched pairs are reduced, the estimated coefficient increases from 0.147 to 0.169. As the caliper increases, the estimated results are, as expected, getting close to the nearest neighbor matching.

Kernel matching uses all the domestically-owned plants that are in the same industry and in the same year to construct a matched control. However, since the matched sample from kernel matching is the least balanced in terms of t statistics among all the matching procedures used in the research, the estimated results are substantially different from others. As will be compared in Section 3.4, the results are similar to conventional linear regression results on unmatched sample. Yasar and Paul (2008) also reported a smaller estimate from kernel matching in case of productivity effects of foreign ownership in comparison of the estimate from the nearest neighbor matching.

There are some variations in the estimated employment growth effects, but the general conclusion about the relationship of foreign acquisition and employment growth does not change. The result is not sensitive to the choice of matching procedures or the choice of the parameters involved, but is sensitive to the balancing property of the matched samples.

3.5 Panel Data Method on Unmatched Samples

As argued in Smith and Todd (2005), the matching estimator is not necessarily the best estimator always and everywhere and that the difference-in-differences matching estimator performs better in their study of the impact of the National Supported Work. Unlike Smith and Todd (2005) and Dehejia and Wahba's (1999, 2002), I do not have experimental results to compare with and thus it is difficult to know which estimator gives the best results. However, I can compare the results from various panel data techniques and those from the matching estimator. The differences in the estimates reveal the difference in identifying assumptions and the characteristics of the data structure.

For comparison purpose, I control for the same vector of plant characteristics as in the matching estimator to study how foreign acquisition affects employment growth. As in the estimation from matching, the sample only contains plants that are acquired by a foreigner once and domestically-owned plants. Plants that have multiple takeovers or domestic takeovers are excluded to avoid bias.

A natural step is to employ ordinary least squares (OLS) as a benchmark comparison. The standard errors are robust to clustering by plants. I also include a comprehensive set of year specific, industry (two-digit ISIC), and region (provinces aggregated into five regions) "fixed" effects to account for factors such as business cycles. Table 3.5 reports the estimates of the variable of interest from various conventional linear regressions. All the equations control for plant characteristics that might affect employment growth. They all have expected signs and are not reported here. The OLS estimate of the effect of foreign acquisition is subsequent growth in employment at a rate 8 percent (since exp(0.077)-1=0.08) faster than in domestic plants. This is almost half of the matching estimate. There are at least two explanations for this. First, OLS regression gives equal weight to all the observations assuming domestically-owned and foreign-owned plants are similarly distributed. This is a strong assumption given the evidence that the two types of plants follow distinctive distributions. Second, the matching estimator does not impose functional form while OLS assumes linear relationship.

To relax the first assumption of OLS, my first experiment is to add the interactions between plant ownership and control variables. This allows the relationship between control variables and the dependent variable to vary across different types of plants. However, it is misleading to interpret the estimated coefficient on the foreign dummy variable when its interaction with the control variables are added. To obtain a meaningful interpretation, the usual practice is to demean the control variables so that the coefficient on foreign acquisition shows its effect on employment growth when all the control variables are held at their averages. The result is an estimate of 23 percentage points (since exp(0.204)-1=0.226) increase in employment growth. Nevertheless, the averages of the control variables for foreign-owned plants are substantially higher than those for the domestically-owned plants in terms of employment, input, energy consumption and labor productivity. Instead of demeaning the control variables, I deduct the mean of the control variables for foreign-owned plants from their original values and then take interactions. The last row of Table 3.5 gives the result. It says, when the control variables are held at the average levels of foreign-owned plants, the foreign acquisition is expected to increase employment growth by 8 percentage points (since exp(0.077)-1=0.08). This is the same as the OLS estimates without interactions.

To exploit the panel nature of the data set (plant X time), the "fixed effects" (or "within") estimator is widely used in the related literature[36]. Table 3.6 presents the results using the traditional panel data methods. The plant fixed effect approach looks at growth in employment within a plant before and after the acquisition and, similar to the difference-in-differences estimator, it removes the time-constant unobserved plant characteristics that could confound the explanation of acquisition effects. The plant fixed effects estimation is carried out with year dummy variables to account for any year specific effects. The plant fixed effect estimate of the foreign acquisition effect is approximately 11 percentage points (since exp(0.100)-1=0.106). This is closer to the matching estimate than the simple OLS estimate. What makes the fixed effects estimator different from the matching estimator is that it in fact uses the pre-acquisition data of foreign-owned plants to impute the counterfactual outcome. In this case, no matching is needed for pre-acquisition. Its identifying assumption is that the unobserved factors that contribute to the employment growth rates should stay constant. In other words, any changes in employment growth rates before and after foreign acquisition are attributed to the takeover since the unobserved factors are differenced out through fixed effects estimation.

The treatment estimator developed by James J. Heckman (1979) is another estimation technique tackling similar sample selection problem widely used in the labor market literature. Foreign acquisition is more likely to happen to plants with better prospect to grow, which results in the sample selection problem known as "cherry-picking" in the literature. The treatment methodology attempts to correct for this selection bias by adding an estimated probability of being selected to the linear model. The assumption for a reliable treatment effects estimate is to include at least one additional regressor in the selection rule. The rationale of this estimator is to

[36] Random effects (GLS) estimator has been experimented since it gives a more efficient estimate when endogeneity is not a concern. It produces a similar result as fixed effects estimate. However, a Hausman test rejects the random effects estimate in favor of fixed effect estimate at the 1% level.

control for the part of the error term in the outcome equation that is correlated with the selection dummy variable. In my estimation, the probability of being selected is estimated with a few more terms than the linear model, such as age and age in squared term. The correlation between employment growth rate and age is merely -0.0369, but age is statistically significant at the 1 percent level in the selection estimation. Also age is used in the probit model for propensity score matching. Table 3.6 tabulates the estimate. The result is much smaller, less than half of the matching estimate, although it still shows a positive and significant effect from foreign acquisition.

The difference in the estimates from Heckman's treatment effects model and the matching approach reflects the difference in identifying assumptions between these two models. The matching estimator adjusts the selection bias by matching on a list of observed plant characteristics and by assuming the unobserved plant characteristics are independent of the selection decisions of foreigners. By contrast, Heckman's treatment effects estimator relies strongly on the exclusion restrictions. The additional regressors in the selection estimation deal with the part of the error term in the outcome equation that is correlated with the selection. By including them in the outcome equation, the impact of treatment from the selection process can be separated. The choice of these additional regressors can be crucial. When I use the propensity score model specification including age, age squared and the employment squared for the selection estimation, the treatment effects estimate produces an even smaller estimate of 0.059 with smaller standard errors. Unlike the surveys in the labor market study, the manufacturing survey may not provide as many variables to satisfy the exclusion restrictions.

Propensity score is a composite score summarizing plant heterogeneity and matching on the propensity score is essentially a weighting scheme, which determines what weights are placed on comparison units when computing the estimated treatment effect (Smith and Todd 2005). The weights depend on the distance of propensity score between the treated and comparison units. One of the traditional approaches to handle plant heterogeneity in econometric models is to use weighted least squares (using plant size measured by employment as the weight, for instance). As firms grow, there is more variability in its employment growth rates, resulting in the violation of homogeneity assumption. Breusch-Pagan test is performed to test the possibility. The null hypothesis of homogeneity is rejected at the 1% level. A plot of the residuals against the fitted values following the OLS estimation also suggests heterogeneity in the regression. So it is important to correct for heterogeneity in the linear regression. Table 3.6 gives the WLS estimate. It is close to the estimate from OLS without interactions, but far from the matching estimate. Although WLS is a more efficient estimate when heterogeneity is present, it only accounts for the heterogeneity in one variable between foreign-owned and domestically-owned plants.

Another common panel method is the Arellano-Bond panel GMM estimator, which controls for the possible unobserved effects that could be correlated with acquisition. If the unobserved effects that determine the better prospect to grow are auto-correlated over time, the Arellano-Bond panel GMM estimator resolves the endogeneity by using the lagged dependent variable and differences of the exogenous variables as the instrumental variable under GMM framework. The rigorous treatment effectively reduces the endogeneity bias and alleviates the issue on the distributional differences between foreign-owned and domestically-owned plants. Table 3.6 reports the results[37]. The result is most close to the matching estimate in comparison to the previous ones. The drawback for the dynamic panel method is that it requires a large number

[37] The Arellano-Bond panel GMM estimation is carried out on plants with foreign takeovers only due to the size constraint.

of cross-sectional observations and that it is time-consuming to calculate. As more large micro datasets are available, the first constraint could be resolved now.

Overall, the results in this section shows that the estimates from matching procedure are most close to fixed effects estimate and the Arellano-Bond GMM estimator. Both fixed effects and difference-in-differences assume the endogenous part of the unobserved error term is time-invariant. The Arellano-Bond GMM estimator treats the autocorrelation of the error term using instrumental variable that alleviates the assumption about the distributional differences between different types of plants. Additionally, with some adjustments, OLS could produce similar results as the matching estimate.

3.6 Dynamics of Effects on Employment Growth

Another advantage of matching estimator is that it allows tracking the path of employment growth following foreign acquisition. In a previous section the matched estimates show that the employment growth rates jump in the year of acquisition and then stabilize at the pre-acquisition level. Now I utilize several other estimation models to check the dynamics of the employment growth effects.

I incorporate dynamics in a number of other ways in Table 3.7. The nearest neighbor matching estimate (with one control unit) from the previous section is presented for comparison. In the analysis of acquisition dynamics, first, to OLS (without interactions) estimation I add a set of dummy variables which are unity if plants are taken over by foreigners in the current year, 1, or 2 years ago. The results on acquisition dynamics are similar to the nearest neighbor matching with three and five control units in Table 3.4. In particular, the coefficient on the takeover in current year is positive, large, and highly significant. The coefficients on other dummy variables are not statistically significant.

If the unobserved effects are serially correlated over time[38], OLS estimates are inefficient. To address this possibility, I experimented with Prais-Winsten estimation which assumes the error term to follow first order auto-correlation. The Prais-Winsten estimates on acquisition dynamics are similar to OLS and matching estimates. Additionally, random effects estimates are shown for further robustness check and the results are robust.

The dynamic estimates from linear regression and various more advanced panel data methods produce similar results as the matching estimates, especially in the year of acquisition. There are some variations in the estimates for other years, although they are statistically insignificant. One of the possible explanations is the magnitude of the employment growth effects in the year of acquisition. Most estimations produce a close to 35 percentage points (since exp(0.3)-1=0.35) increase in employment growth rates. It is likely that the estimate is not sensitive to the estimation methods when it is economically large and statistically significant.

3.7 Conclusions

The combination of propensity score matching and difference-in-differences is first used in the study on program evaluation or labor market outcomes. Now it has become widely adopted in the literature of foreign acquisition where similar sample selection and endogeneity issues exist. Although a number of studies have been conducted to compare the matching

[38] I run AR(1) on the residuals from OLS estimates and the estimated coefficient is -0.15 and it is statistically significant at 1% level.

estimates and a few other non-experimental methods with the experimental results in program evaluation literature, there is no previous research comparing the estimation results between matching and other regression methods in the literature of foreign acquisition.

A number of matching methods with different parameters have been experimented to estimate the average employment growth effects of foreign acquisition in case of Indonesian manufacturing plants. The results are robust to the matching procedures and to the choice of parameters involved in each matching procedure. When the matching estimates are compared with the estimates from other conventional panel data methods, they are much closer to the fixed effects estimate and the Arellano-Bond GMM estimate. In the analysis of employment growth dynamics following foreign acquisition, both matching estimation and other regression models produce similar results.

The paper does not attempt to find a “fit-all” econometric model for the foreign direct investment literature. Rather, through comparing various methodologies, it reveals the strength and weakness of each method. The combination of propensity score matching and difference-in-differences method provides another powerful tool for the literature, but it is always wise to experiment with various other methods with different identifying assumption to check the robustness of the results.

Figure 3.1: Comparing Distributions of Plant Characteristics by Ownership

Figure 3.2 Distributions of Plant Characteristics, Matched Sample, NN, n=1

Figure 3.3 Distributions of Plant Characteristics, Matched Sample, Caliper=0.00001

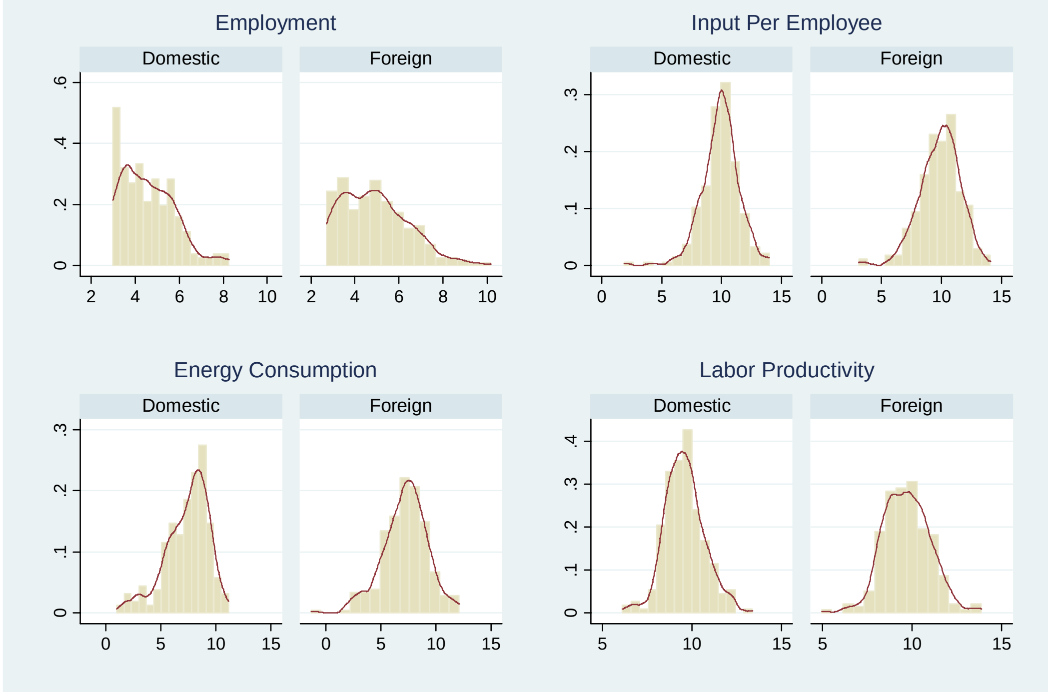

Table 3.1: Relative Plant Characteristics of Foreign-owned over Domestically-owned Plants by Industry[1], 1975-2005

	Employment	Input Per Employee	Electricity Consumption	Labor Productivity
All Industries	*1.38*	*1.16*	*1.22*	*1.17*
31. Manufacture of Food, Beverages and Tobacco	1.40	1.20	1.39	1.23
32. Textile, Wearing Apparel and Leather Industries	1.54	1.14	1.14	1.13
33. Manufacture of Wood and Wood Products, Including Furniture	1.34	1.09	1.14	1.07
34. Manufacture of Paper and Paper Products, Printing and Publishing	1.21	1.15	1.14	1.13
35. Manufacture of Chemicals and Chemical, Petroleum, Coal, Rubber and Plastic Products	1.22	1.13	1.13	1.15
36. Manufacture of Non-Metallic Mineral Products, except Products of Petroleum and Coal	1.45	1.25	1.38	1.23
37. Basic Metal Industries	1.02	1.08	1.10	1.10
38. Manufacture of Fabricated Metal Products, Machinery and Equipment	1.32	1.12	1.15	1.14
39. Other Manufacturing Industries	1.47	1.08	1.12	1.10

1. The table shows the ratio of each plant characteristics for the foreign-owned plants relative that for the domestically-owned plants.

Table 3.2: Probit Model: Propensity Scores

Dependent Variable	Foreign Ownership
Age	-0.135***
	[0.006]
Age Squared	0.003***
	[0.000]
Employment	0.582***
	[0.067]
Employment Squared	-0.035***
	[0.006]
Inputs	0.017*
	[0.009]
Energy	0.022***
	[0.008]
Productivity Before Acquisition[1]	0.085***
	[0.013]
Ratio of White-collar Workers	0.435***
	[0.075]
Year Effects	Y
# of Observations	306,456
Chi-squared	2,249
Pseudo R-squared	0.1779

1. Productivity at one-period before acquisition.

Table 3.3: Balancing Test between Foreign-owned Plants and Domestically-owned Plants

		Means		t-test
Variables	Sample	Treated	Control	t-stat
Age	Unmatched	5.13	10.07	-21.50
	Matched (NN, n=1)[1]	8.45	7.92	1.51
	Matched (Caliper, Caliper=0.00001)[2]	10.60	9.61	1.92
Age Squared	Unmatched	58.19	150.23	-14.98
	Matched (NN, n=1)[1]	112.37	102.94	0.94
	Matched (Caliper, Caliper=0.00001)[2]	154.60	135.91	1.29
Employment	Unmatched	5.01	4.17	22.11
	Matched (NN, n=1)[1]	5.04	4.86	2.30
	Matched (Caliper, Caliper=0.00001)[2]	4.93	4.60	3.12
Employment Squared	Unmatched	26.66	18.73	21.36
	Matched (NN, n=1)[1]	27.11	25.14	2.37
	Matched (Caliper, Caliper=0.00001)[2]	26.47	22.53	3.44
Inputs	Unmatched	7.62	6.66	14.71
	Matched (NN, n=1)[1]	7.41	7.61	-1.62
	Matched (Caliper, Caliper=0.00001)[2]	7.20	7.36	-0.89
Energy	Unmatched	10.23	9.38	15.95
	Matched (NN, n=1)[1]	10.11	10.19	-0.69
	Matched (Caliper, Caliper=0.00001)[2]	9.88	9.90	-0.16
Productivity at t-1	Unmatched	9.99	9.11	23.18
	Matched (NN, n=1)[1]	9.96	9.91	0.63
	Matched (Caliper, Caliper=0.00001)[2]	9.72	9.58	1.32
Ratio of White-collar Workers	Unmatched	0.20	0.15	9.02
	Matched (NN, n=1)[1]	0.22	0.20	1.07
	Matched (Caliper, Caliper=0.00001)[2]	0.21	0.19	1.53

Note:
1. Nearest neighbor matching, the number of controls is one (n=1);
2. Caliper matching, the maximum distance between the matched pair is 0.00001.

Table 3.4: Sensitivity of Matching to the Specification of Matching Procedure[1,2]

Matching Procedure	3-year Average	5-year Average	Year of Acquisition	One Year After Acquisition	Two Years After Acquisition
Nearest Neighbor					
n=1	0.147***	0.137***	0.297***	0.038	0.003
	(0.0325)	(0.0306)	(0.0533)	(0.0459)	(0.0509)
n=3	0.168***	0.158***	0.338***	0.017	-0.030
	(0.0285)	(0.0281)	(0.0480)	(0.0363)	(0.0370)
n=5	0.137***	0.128***	0.333***	0.018	-0.041
	(0.0259)	(0.0257)	(0.0441)	(0.0334)	(0.0353)
Caliper					
Caliper=0.00001	0.169***	0.147***	0.353***	-0.001	-0.045
	(0.0430)	(0.0408)	(0.0705)	(0.0549)	(0.0602)
Caliper=0.00005	0.133***	0.113***	0.279***	0.014	-0.024
	(0.0374)	(0.0354)	(0.0589)	(0.0540)	(0.0582)
Caliper=0.0001	0.151***	0.138***	0.302***	0.014	-0.007
	(0.0353)	(0.0334)	(0.0568)	(0.0499)	(0.0591)
Kernel[3]	0.063***	0.049**	0.244***	-0.051	-0.114
	(0.0241)	(0.0234)	(0.0420)	(0.0302)	(0.0290)

1. Each column gives the results when different outcome variable is defined. When the average of 3 year post-acquisition is defined as the outcome variable, the average of 3 year pre-acquisition is the pre-treatment period.
2. Standard errors are bootstrapped.
3. I chose Gaussian kernel and the bandwidth is 0.06.

Table 3.5: OLS Estimation of Employment Growth Effects of Foreign Acquisition

Model Specification	Foreign Acquisition
Matching Estimator[1]	0.147***
	(0.0325)
OLS Without Interactions	0.077***
	(0.0061)
OLS With Demeaned Interactions	0.204***
	(0.0176)
OLS With Adjusted Interactions[2]	0.077***
	(0.0070)

1. The estimate is estimated by nearest neighbor matching with one control and the variable of interest is the three-year average of employment growth.
2. The interactions are adjusted by deducting the mean of the control variables for the foreign-owned plants from the values of the control variables for all the plants. This way the estimated coefficient on the foreign acquisition gives the employment growth effects of foreign acquisition when the control variables are held at the averages of the control variables for foreign-owned plants.

Table 3.6: Effects of Foreign Acquisition on Employment Growth, Panel Data Methods[1]

Estimation Methodology	Foreign Acquisition
Matching Estimator[2]	0.147***
	(0.0325)
Fixed Effects	0.100***
	(0.0155)
Treatment MLE	0.063***
	(0.0077)
Weighted Least Squares (WLS)	0.084***
	(0.0179)
Arellano-Bond panel GMM	0.179***
	(0.037)

1. The table reports the estimated results of the parameters of interest, foreign acquisition. The dependent variable is the employment growth. Robust standard errors (clustered at plant levels) are reported in parentheses.
2. The estimate is estimated by nearest neighbor matching with one control and the variable of interest is the three-year average of employment growth.

Table 3.7: Dynamic Analyses of Employment Growth Effects of Foreign Acquisition

Primary Parameters of Interest	Matching[1]	OLS	Prais-Winsten	Random Effects
Year of foreign acquisition	0.338***	0.311***	0.317***	0.294***
	(0.0480)	(0.0349)	(0.0348)	(0.0344)
Foreign acquisition 1 year ago	0.017	0.0195	0.0216	0.0120
	(0.0363)	(0.0154)	(0.0154)	(0.0152)
Foreign acquisition 2 years ago	-0.030	-0.0054	-0.0034	-0.0120
	(0.0370)	(0.0180)	(0.0182)	(0.0178)

1. The estimate is estimated by nearest neighbor matching with one control and the variable of interest is the three-year average of employment growth.

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